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Using Satellites to Make Index Insurance Scalable:

Final IRI Report to the International Labour Organisation - Microinsurance Innovation Facility

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The International Labour Organisation is a specialized agency of the United Nations.

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CHAPTER

ONE

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CHAPTER

TWO

OVERVIEW

This report is the final narrative deliverable for the ILO's Microinsurance Innovation Facility contract to the International Research Institute for Climate and Society at Columbia University "Using Satellites to Make Index Insurance Scalable" PG004060, ILO CU11-0558.

In this project, we have utilized the case study of the R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) project [1] in Tigray Ethiopia to address the following Learning Agenda Questions (LAQs).

1. **Science perspective:** *How can satellite imagery of vegetation be used to cross-check current index insurance products?* To what extent do they reduce basis risk (disagreement between index payouts and actual losses) by improving products and appropriately identifying locations with payouts in loss years?
2. **Provider perspective:** *Under what circumstances are vegetative remote sensing technologies replicable and scalable?* What are the efficiency gains for providers? Under which circumstances, for which crops and areas are they accurate?
3. **Client perspective:** *What is an added value for clients of using vegetative remote sensing technologies?* To what extent and when can they be used to protect clients from inappropriate and non-functioning contracts? What is their potential to make the products more affordable, particularly in data poor environments?

To study these questions, we have developed and tested a methodology for using satellite technologies to check indexes in a large scale insurance project, which makes payouts triggered by satellite rainfall estimates. The example used as a case study in this report is the R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) project, which has 83 sites across northern Ethiopia. The R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) project has been offering insurance since 2009, growing to large scale in 2011. Farmers have experienced normal, good, and bad years, which allows us to understand where the index is functioning well and where it must be improved.

Our study is intended to provide outputs potentially valuable for providers and clients, including (re)insurance companies, NGOs, humanitarian organizations, policy makers, the academic community and farmers who are interested in index insurance mechanisms, applications and reliable scalability. Although our project explores a particular case, the general lessons are applicable to a much wider range of projects, with verification approaches that could be valuable to insurance projects that utilize ground measurements or area yield for payouts. The specific technical approaches used in this study are examples of a particular case illustrating a generalizable verification approach. The basic lesson is not to follow the particular solutions selected here, but instead to apply the general approach to understand and effectively apply the verification solutions most appropriate for your index insurance project.

One of the challenges of increasing project scale is the increased burden it puts on the ground network. Large scale index insurance projects like R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) depend heavily on an on the ground network of clients, experts, site visits and partners for continuous verification and improvement of products. Verification technology may be able to reduce the information burden on these networks by

[1] The R4 Rural Resilience initiative is a partnership between the UN World Food Programme and Oxfam America launched in 2010, December. The program builds on the initial success of HARITA (Horn of Africa Risk Transfer for Adaptation), an integrated risk management framework developed by Oxfam America, the Relief Society of Tigray (REST), together with Ethiopian farmers and several other national and global partners to enable poor farmers to strengthen their food and income security through a combination of improved resource management (risk reduction), insurance (risk transfer), microcredit (prudent risk taking), and savings (risk reserves).

focusing ground-truthing efforts on the places that have the most technical challenges, and by strengthening the ability of the on the ground network to anticipate, understand, and resolve issues. Eventually vegetation satellite imagery may be developed sufficiently to identify potential problems before the insurance is rolled out, exploring and resolving them before they are experienced by the project clients.

In this study we tested verification methods by studying the experiences of an existing project, checking to see if the methods we have developed would have identified potential issues. Through this experience, we have learned the following general lessons:

We have been able to successfully use satellite imagery of vegetation to improve the verification process for a large scale index insurance project.

The satellite vegetative image methodologies have been successful–clearly identifying the places in the R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) where the disagreement between index payouts and actual losses (basis risk) was found to be the highest. We have explored a range of specific technologies, identifying the ones that are most effective, and most directly applicable to the R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) project. The verification approach identified the only region that experienced substantial problems due to the satellite rainfall index itself.

We have performed a series of analyses to identify weaknesses in the technologies, and to better understand what they indicate, so that their results can be more effectively used in solving index problems. We have applied a series of diagnostics that link the satellite vegetation imagery to what is actually on the ground. We have used rare, high quality imagery to cross-check and understand common, lower resolution satellite imagery. Additionally, experts have performed ground verification to validate and understand the high quality imagery. Through these effort, when checking for mismatches with indexes, we have arrived at practical ways to link farmer interviews to cutting edge satellite research.

Vegetation indexes appear to work well in validating hazards that are the most widespread, but can miss other important problems.

In R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA), *vegetation indexes identified insurance indexes that had problems during the end of the rainfall season.* Lack of rainfall at the end of the season is a risk to which all insured crops are vulnerable. However, farmers face other important hazards as well. Using satellite vegetation imagery to check indexes is effective for the most common problem across crops and regions, but not for the coverage specific to only long cycle crops. For example, we were not able to reveal a simple application of satellite vegetation imagery to effectively check indexes targeting rainfall problems at the beginning of the rainfall season. This is one of the hazards that impacts a subset of crops, the “long cycle” crops, which include sorghum, maize, barley, and wheat.

Although the **satellite index insurance appeared to be functioning** for the beginning of the season, the **satellite vegetation verification approach we tested was not effective** in checking the quality of the insurance index in that period and the project needed to rely on other verification approaches. Providers, knowing that vegetation indexes can identify the insurance indexes that have problems at the end of the season, can better allocate on the ground resources to target the most universal issues for the end of the season. However, providers would not have as much useful information for the beginning of the season using the vegetation satellite technologies we tested. Other options for validating this hazard should still be explored. It may be that a more sophisticated application of satellite vegetative imagery would be effective, or it may be that a completely different technology must be utilized.

We have found that satellite imagery of vegetation can improve the coverage quality and lower the cost of the products offered to clients.

The satellite technologies studied here allow the project to spend less resources on expensive on the ground validation and instead target resources to the most challenging places. Since the technologies have been effective across the entire project region and for problems that impact all of the crops, they can be used in the most challenging places. The satellite technologies identified the indexes that needed further study, thus demonstrating that they could be used in future projects to identify and fix issues before insurance products are sold. Although the satellite verification approaches were not effective in flagging all issues, they identified the most geographically and agriculturally widespread ones, providing the biggest opportunity for reducing costs through more effective use of expensive on the ground validation activities.

The following sections outline and elaborate on the key messages and lessons learned, and provide supporting evidence. Additional detail on remote sensing products and methods used is also discussed.

Note that many of the tables included are the raw output of the project insurance design and verification software, so they often do not have polished formatting and may include information not directly discussed.

CHAPTER THREE

LEARNING AGENDA QUESTIONS

3.1 Overview

- The limited number of rain gauge networks means that index insurance is not scalable if it only works in areas covered by existing rain gauges with long histories.
- Remote sensing is likely to be key in scaling up index insurance schemes to a point where they can meaningfully address poverty. Several schemes have already shown potential.
- There are many types of satellite-derived product available, each with their own strengths and weaknesses. Here we have focused on two particular families: satellite rainfall estimates and estimates of vegetative health.
- Although success with satellites has allowed index insurance programs to expand, remotely sensed data can often have large inaccuracies and it certainly cannot be applied blindly over all landscapes.
- Satellite based index insurance require comprehensive validation processes, which may be beyond the capacity of a project's ground-based activities, particularly as projects reach large scales.
- Satellite vegetation estimates may hold promise as a validation source for index insurance, including large scale projects using satellite estimation of rainfall for the index insurance payouts.
- The aim of this project is to explore the role that different remote sensing products can play in the index insurance verification process and to study how they might be best applied practically in index insurance projects, using the R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) large scale index insurance project as a case study.

3.2 Science Perspective (LAQ 1)

- We have found that the satellite vegetative image methodologies were successful in identifying the places in the R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) where the basis risk (disagreement between index payouts and actual losses) was found to be the highest.
- We have found that it is possible to use remotely sensed estimates of vegetation (e.g., MODIS EVI) to check the locations where the satellite rainfall driven R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) contract is working best, and where it is not working as well.
- The vegetation products (EVI and NDVI) had good agreement with ARC satellite rainfall estimate that triggers the index insurance for the late window but did not have a good agreement for the early window.
- The vegetation products were better at identifying extreme drought, and were less effective at accurately detecting drought during less extreme years.

- Of all the products tested, we found that there was the best agreement between the satellite rainfall index for a standard modern vegetation product known as the Enhanced Vegetation Index, or EVI (using the MODIS satellite) and ARC satellite rainfall estimate.
- We found that the alternative satellite rainfall product (TAMSAT) had close, but not perfect agreement with the satellite rainfall estimate used for the index (ARC).
- We found that there was less agreement in identifying the low rainfall years with the merged rain gauge/satellite rainfall estimate (ENACT) and the satellite estimate (ARC) used for the insurance index.
- The alternative satellite rainfall product (TAMSAT) and merged product (ENACT) provide one avenue for validating the early window for rainfall, in case the vegetative products cannot be improved sufficiently to be useful and another alternative is not found.
- A lag of one month between the occurrence/lack of rainfall and detecting this event using a vegetation index was found to be most appropriate. Plants take some time to respond to rainfall.
- The change in area over which the vegetative data was averaged did not substantially affect the agreement between the vegetative and the rainfall products.
- In general, farmer recall and available historical regional yield data agree on the major drought years in the past decade or so, and are generally consistent with index payouts and vegetative sensing for major events across most of the region.
- Using high-resolution Landsat satellite imagery, we were able to link individual land-types (e.g., trees, scrub vegetation, agricultural fields) and the vegetation index values provided by MODIS EVI. We found that EVI was effective at representing the fraction of vegetation coverage of the satellite images.
- It may be possible to improve our use of EVI through knowledge of the vegetation fraction within the area for each datapoint (pixel). Although our quick diagnostics did not find immediate improvements, it is possible that with more work we will eventually better understand droughts by paying more attention to pixels that have more vegetation than those with mostly bare earth.
- Overall the 2012 indexes effectively represented the local experiences during the growing season, and the contracts performed well for the vast majority of farmers.
- Based on the R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) experience in 2012 we have more confidence in the performance of the EVI ranking technique for the late window because it might be able to preemptively flag issues before a product is brought to market.
- We found that some regions showed a closer relationship between rainfall estimates and EVI than other (e.g., a higher ranking coefficient). Using maps of the ranking coefficient, it was possible to select villages, which had complained about their ARC contracts - this clearly shows the promise of the verification approach.
- In the R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) case study, we have found that all of the index issues identified and addressed by clients and experts through the project feedback process during the drought of 2012 occurred in villages that were flagged by the satellite vegetation cross-checking process. This suggests that this process has the potential for proactively identifying issues in future indexes and addressing them before they are brought to market.

3.3 Provider Perspective (LAQ 2)

Satellite imagery has been found to be useful in cross-checking insurance indexes on a large scale project for the dominant hazards across the entire project area. The satellite cross-checking process does require some targeted ground and vicarious validation analysis in order to be effective. Because expensive validation analysis is less than would be necessary for careful ground validation of all project sites, the satellite process allows providers to reduce costs by targeting expensive validation resources to areas flagged by the satellite vegetation imagery and hazards identified by the on the ground project network. By improving product validation, the provider can offer improved products for a given budget, and reduce index errors and client complaints. This can also reduce costs resulting from resolving client issues due to indexes missing important payouts.

3.4 Client Perspective (LAQ 3)

For the clients, the use of satellite vegetation imagery in cross-checking insurance contracts provides the potential for indexes that better protect them from hazards. By catching many of the potential issues in indexes before they are offered, the vegetation imagery provides the possibility of having the issues in indexes identified and resolved before the insurance product is brought to the market. Because the satellite cross-checking appears to be effective at reducing product validation and design expenses, it also has the potential to reduce the insurance cost that clients face.

In the rest of this report, we will elaborate on these lessons, provide more background, and discuss the details of the range of diagnostics, comparisons, and analyses that we have done.

CHAPTER

FOUR

MOTIVATION, BASIC APPROACH AND MAIN FINDINGS

4.1 Background

4.1.1 Challenges

Index insurance projects are growing from small pilots with hundreds of farmers to implementations with many tens of thousands of farmers. **The lack of comprehensive rainfall and crop data is a key constraint in scaling insurance.** Current rainfall data is needed to calculate payouts while historical data is necessary to design the insurance and calculate the price of the insurance. Initially, rain gauge networks formed the basis of most pilot index insurance programs. However, in developing countries rain gauge networks tend to be sparse and unevenly distributed, with most gauges located in towns and cities–not farms. Even if enough new rain gauges could be installed, there would not be enough historical data to design and price insurance products. Index insurance is not scalable if it only works in areas covered by existing rain gauges with long histories.

Scarcity of agricultural data also restricts scaling. For example, crop yield data is important for designing and validating the index but coverage for crop loss is often only available at a regional level and can be limited by short historical time-series and measurement inaccuracies. This "data-poverty" challenge is one of the key constraints for index insurance. **Many have hoped that remotely sensed data from satellites can provide the weather and crop data needed for index insurance at large scales**.

Although success with satellites has allowed index insurance programs to expand, remotely sensed data can often have large inaccuracies and it certainly cannot be applied blindly over all landscapes. Unlike a rain gauge or a yield measurement, satellites do not directly measure rainfall or vegetative growth, instead inferring this information from visible/infra-red brightness temperatures or microwave emissions. Satellite vegetation indexes have well-documented limitations when used to estimate yields. These include errors from dust, clouds, solar angle and satellite angle. In addition, satellites often perform differently over different landscapes. Individual pixels capture a mix of farmland, bare earth, trees and grasses. For example, a vegetation index must be interpreted carefully depending on whether it is looking at farmland, savannah or deep forest. For both rainfall and vegetation, one side of a mountain range may be fundamentally different from the other. It is critical to understand the accuracy of the satellite estimations. However, in many insurance projects, no attempt is made to quantify the uncertainty in the satellite estimates. Unfortunately, this typically occurs in regions where satellite information is needed the most because there is the least ground-based data.

The potential errors in satellite products present a significant barrier to the further expansion of index insurance projects. Remote sensing is a relatively new field, and produces huge amounts of data. Processing and finding errors in this data is a new frontier in research. If satellite products are not verified for large-scale insurance projects, large numbers of farmers may be hurt by products that do not work. The solution to this issue in the past has been to perform extensive on-site ground verification.

Current projects are required to undertake costly and time-consuming physical validation of the indexes on-site by experts, rendering further scale up prohibitively expensive. Large scale index insurance projects like R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) depend heavily on an on the ground network of clients and each year we learn a lot through project experiences as thousands of farmers provide feedback on how the product performed. **One of the challenges of increasing project scale is the increased burden it puts on the ground network of farmers, experts and partners, as it reaches new places, and updates an increasingly large number of products.**

4.1.2 History

IRI has helped design early indexes using satellite vegetation measurements, working with SwissRe and the Millennium Villages Project (MVP) in 2007. The project investigated development of a reliable index insurance product based on satellite vegetation measures. Through the MVP sites, a relatively large amount of data for product design and verification was available, and teams of researchers were stationed at each location to provide necessary on-site information. By the end of the project, we found that the best approach was to target loss through a regional index that combined satellite vegetation sensing with ground-based rainfall measurements, so that each measure could fix the problems of the other (see p.56 of the CSP2 at iri.columbia.edu/csp2 for more details) [CSP2]. The extensive groundwork required to check the index meant that it was too expensive to scale up into a stand-alone farmer product.

The R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) project is an example of recent satellite-based index insurance work that we have been involved in. By using satellite rainfall estimates to trigger index insurance payouts, the R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) project was able to insure very low-income farmers in locations with limited rain gauge coverage and historical rainfall information. Initially reaching approximately 200 farmers in 2009, it has been able to quickly scale, reaching nearly 20,000 small-scale farmer households in just three years. Indexes have been designed for 83 villages, and offered in 77 villages. For this study, we focus on the sites in Tigray, which represent most of the villages in the project, shown in Figure 4.1. (See www.oxfamamerica.org/files/r4-annual-report-2012.pdf for more details [OxfamReport].) Because this process has involved time consuming and expensive physical validation of indexes at sites in order to double check the continued accuracy of products as the project grows, the satellite validation processes described in this report have the potential to reduce scaling challenges (for details about the product design process see [IRI-OxfamReport2009], [IRI-OxfamReport2010]).

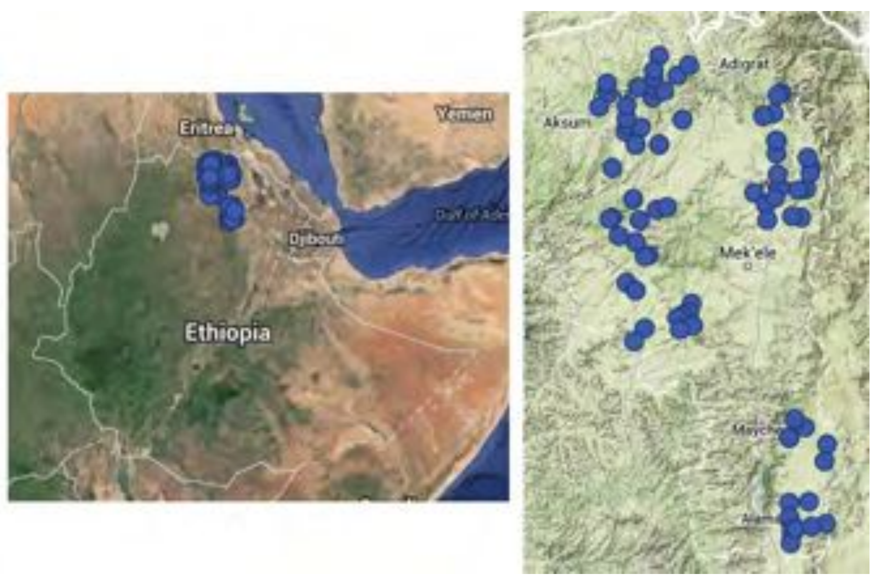

Figure 4.1: Ethiopia R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) map. The locations of the insured sites within the R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) insurance project.

The intent of R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) indexes is to provide a meaningful payout for the major drought problems that impact an entire village, with other R4 risk reduction or risk sharing efforts targeting the smaller, more individual level problems. The project targets problems such as the rainfall season ending early, which typically overwhelm other risk sharing strategies (e.g., people who have lost their crop borrow money from relatives who have experienced a good harvest year).

Two dominant issues were identified that explain the major crop losses: an unfavorable beginning and/or end of the rainfall season. To address these hazards, indexes in each R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) village are designed for two parts of the season: the beginning of the rainy season (around March/April/May) and the end of the rainy season (around August/September). Throughout the rest of this report we refer to the season of an index as either 'early' or 'late,' respectively. As shown in Figure 4.2, the specific timing of these windows is village specific. The top two panels show how the early window start and end dates differ across the different R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) sites. The bottom two panels show how the late window start and end dates differs between the different sites.

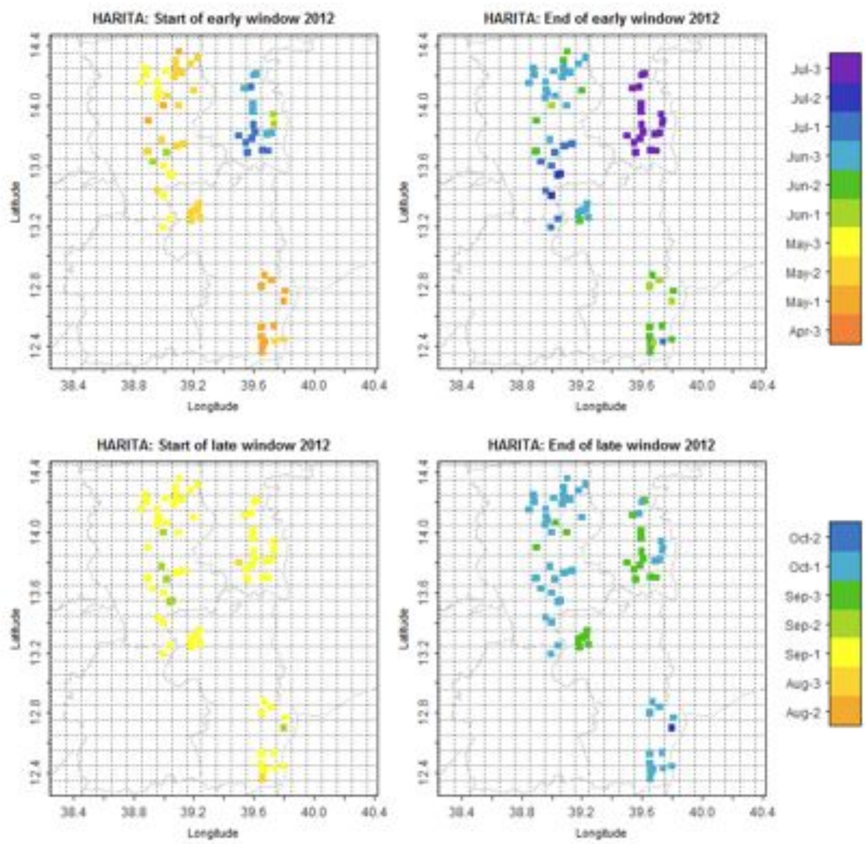

Figure 4.2: Ethiopia R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) window plot. The timings of the early and late windows in the project sites.

The insurance payouts are triggered using the NOAA CPC ARC satellite rainfall estimate, recently upgraded to ARC2 with has an extended historical database, going back to 1983.

The R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) index is effective at targeting the major large scale droughts. For the two largest regional droughts that occurred in the 2000s, the droughts of 2004 and 2009, the index would have triggered in nearly all of the project sites. In a typical insurance product, it is rare to have more than a one in five year payout, so agreement in those years shows that the satellite index is doing about as well as is expected for most insurance products. This provided much of the confidence for the project to move forward with the index. However, not all insurance projects will be verifiable through large scale droughts. Insurance could be reliable and effective even if droughts are more localized. One of the central problems we address in this report is to find ways to understand if an index can effectively target more localized droughts, or if an index is only reliable for very large scale events.

4.1.3 Basic Approach: Bad year rankings and cross-checking

In this project we tested approaches for how different remote sensing products could help in the index insurance verification process. Our task was to develop and test checks that can identify the subregions where there may have been problems with the index, so that the project network of experts could focus their attention and resources on those places. We focused on analyses and products that could be most quickly, easily, and cost effectively integrated into practical operations led by local implementers, tools that link directly to the discussions, expertise, and information present on the ground in these projects. We developed and tested a practical set of cross-checks and diagnostics that could allow satellite technologies to be integrated directly into the index design and verification, as well as into the response to complaints, and annual product updates.

The key to solving the issues described earlier lies in the variety of satellite products available to users, each with their own strengths and weaknesses. Each of the different products can provide a new piece of information about conditions on the ground, reducing the need for physical validation. For example, a vegetation index might be able to indicate locations where a satellite rainfall estimate is (or isn't) adequately capturing drought years. Achieving this requires a greater understanding of the relationship between vegetation data and rainfall estimates.

Satellites may be best used in insurance to measure simple but important things. For example, satellites can show if there were any rain clouds over a village, or if the vegetation across the whole landscape turned brown earlier than usual, indicating that the rainfall season in a village ended early and crops failed. We also include some of the ground-based checks in order to understand how the satellite based-validation is corroborated by the client feedback information, and to get a general sense of how much the complete package of information available leads to common conclusions. **The value of this verification approach is to reduce the information burden on the on the ground networks** by focusing the limited attention to the places that have the most technical issues to resolve, focusing and strengthening the ability of the on the ground network to anticipate, understand, and resolve issues. One challenge in index verification is that the metrics utilized by scientists for verification are often not understood by clients and agents in the field, and that often observations by clients and field partners cannot be easily integrated into the verification process. This is particularly important for a large scale project, that may have to address farmer complaints from thousands of farmers in dozens of villages in a short timeline to meet deadlines for the following year's rollout.

In this study we focused on the number of "bad" years that match in the historical record. This measure can effectively utilize much of the practical information available in real-world projects, such as yield statistics with limited accuracy, expert and farmer assessments of yields, regional aggregate production or hunger problems, etc. It can easily be communicated with farmers and non-technical partners in the field, who can provide feedback in the same structure. Because each product is in different units, comparisons in this report are presented by ranking each dataset from its lowest predicted rainfall (or vegetation index) year to its highest rainfall (or vegetation index) year, and then by comparing the order of these rankings across satellite products. Typically, we determined "bad" years by counting how many years were ranked in the bottom of both types of satellite products (e.g., Figure 4.3). For this diagnostic analysis we have built software to: 1) query satellite databases (obtained through the IRI Data Library), 2) to assemble information from a wide range of different sources, and 3) to perform an initial assessment of the level of agreement between different data sources across all of the 83 R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) project sites. Comparison across all of the sites, for which indexes have been developed, provides a baseline through which we can learn about the potential opportunities and challenges that lay ahead. Although they are effective, and easy to link to farmer discussions and available data, our rankings are only a starting point. It is likely that they can be improved and generalized.

In the places where there is agreement, we have improved confidence that both tools might actually be capturing important droughts. If there is disagreement, further validation and followup may be necessary. Determining if the index or the verification source or both are wrong is important. Investigation is needed to help fix problems in the index before we can have confidence in the product. Since satellite experts cannot visit every village in a large scale project, every possible elimination of false problems can help reduce costs.

When there is disagreement between a satellite index and a data source, we do not know whether there is a problem with the index, or if the data source is inaccurate in identifying bad years. A data source that is less effective in accurately identifying bad years will have less agreement with the index–unless the data source and the index are both vulnerable to the same problem. If we have reasons to believe that a data source is more effective for accurate

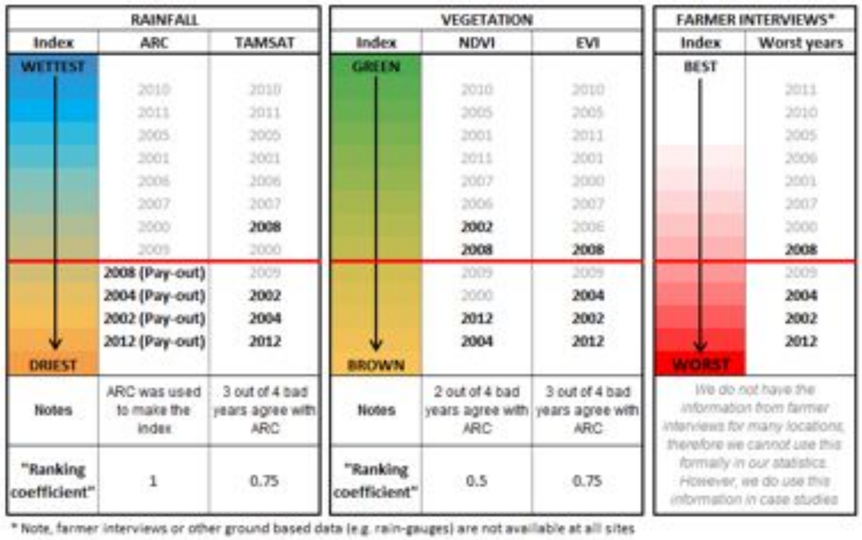

Figure 4.3: A hypothetical example of how the ranking coefficient can be calculated for four satellite products (ARC and TAMSAT for rainfall, NDVI and EVI for vegetation). Note, this schematic uses mock data.

verification, when we see better agreement between an index and the validating data source, we therefore take that as a suggestion that the data source may truly be preferable, at least in that particular situation. It is important to keep in mind that blindly searching for high levels of agreement may over-fit our verification processes to the indexes, where the data analysis process leads us to select verification data sources that have the same vulnerabilities as the index.

4.2 Comparison of range of satellite vegetation, satellite rainfall estimate, and merged datasets

The index insurance payouts in the R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) projects are determined based on an ARC satellite rainfall estimates. Figure 4.4 shows the size of the 10km x 10km area for each datapoint (pixel) on the grid of the ARC satellite rainfall estimate used for the index over the village of Adi Ha. The blue push-pin marks the center of the village, while the yellow pushpins indicate the locations of nearby rain gauges. The size of the pixel is convenient in that it often represents an entire village and its associated agriculture. In this application the satellite technology compliments the existing portfolio of risk management activities, because its resolution provides a level detail that is useful for insurance.

We performed a series of checks on how vegetation satellite products (EVI and NDVI) ranked bad years as compared to the satellite rainfall index (ARC). We also included an alternative satellite rainfall estimate product (TAMSAT), as well as a product that merges satellite rainfall estimates with ground-based rain gauge data (ENACT).

For vegetation sensing, the strategy was to interpret the landscape's response to the arrival of (or lack of) rainfall necessary for crops to grow. Because satellites have different resolutions, we wanted to have the vegetative measurements represent the same region that the satellite rainfall estimates represent. We therefore averaged the vegetative index over the area represented in the satellite rainfall estimate. Figure 4.5 shows the different sizes of the satellite measurement grids (pixels). The largest pixel is the 10km x 10km ARC satellite rainfall estimate that triggers the index insurance. The second largest pixel is an older vegetative index satellite product (AVHRR) that is no longer in operation, but that has images since the 1980s. The tiny dark green square under the yellow pushpin is the 250m x 250m pixel for the vegetative products we use, derived from MODIS satellite observations.

When we compare vegetation remote sensing with the satellite rainfall estimates, we look at the month following the rainfall window of interest. This lag-time is intended to better capture the vegetation response ("green-up", or "brown-out", etc.) to the rainfall experienced during the essential periods for crop growth.

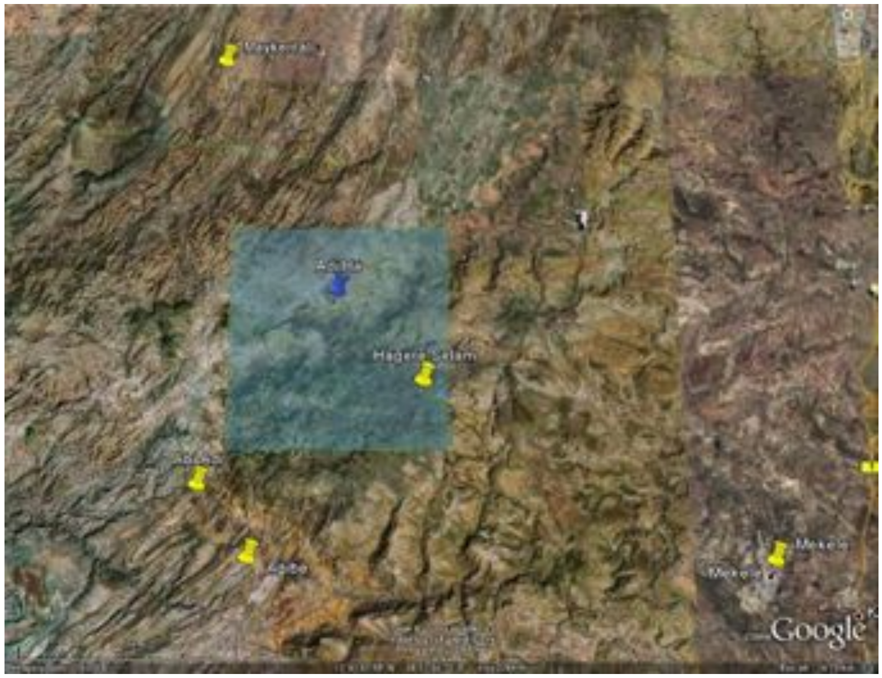

Figure 4.4: Satellite Rainfall Estimate Coverage over Adi Ha Village

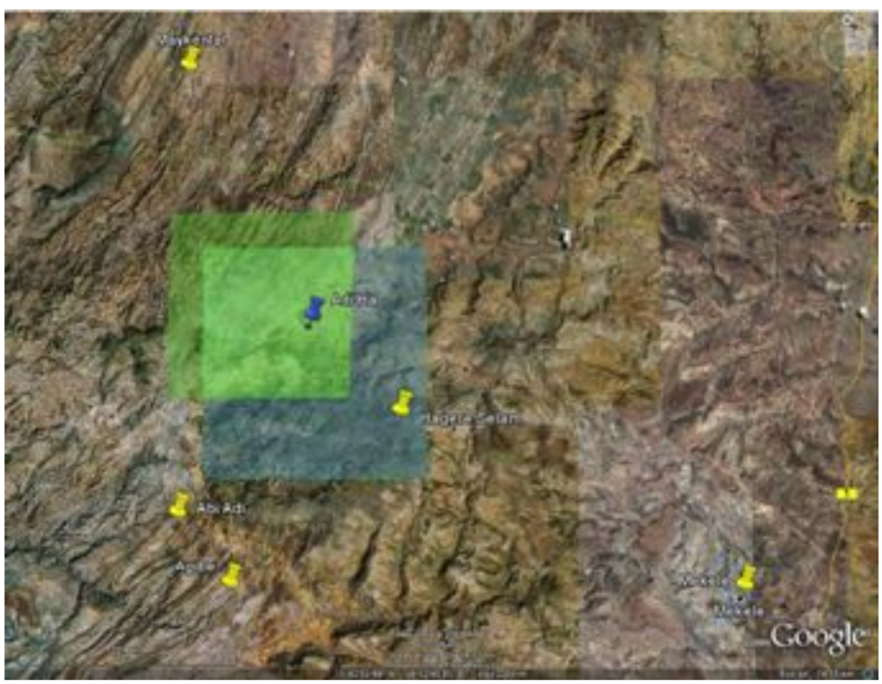

Figure 4.5: Satellite Rainfall Estimate and Satellite Vegetative Imagery Pixel Size

The following bullets summarize the main findings of the comparison.

- The vegetation products (EVI and NDVI) had good agreement with ARC satellite rainfall estimate that triggers the index insurance for the late window but did not have a good agreement for the early window. This is consistent with our expectations, since the vegetation products have been designed to estimate the health and vigor of foliage, and can often be confused by bare soil. At the beginning of the rainfall season there is little foliage and a lot of bare soil, while at the end of the rainfall season, the soil is covered by a lot of foliage.
- Of all the products tested, we found that there was the best agreement between the satellite rainfall index for a standard modern vegetation product known as the Enhanced Vegetation Index, or EVI (using the MODIS satellite) and ARC satellite rainfall estimate. This was expected, since EVI is designed to correct for errors that have been identified in the other, older products, such as NDVI.
- We found that the alternative satellite rainfall product (TAMSAT) had close, but not perfect agreement with the satellite rainfall estimate used for the index (ARC). Since the two products use the same satellite, we would expect them to be somewhat similar. It is valuable that they have some differences, because their different calibrations may help identify places where satellite rainfall estimates do not behave predictably. In addition, having two different products provides a check for the download and data processing errors that can occur when using remote sensing data.
- We found that there was less agreement in identifying the low rainfall years with the merged rain gauge/satellite rainfall estimate (ENACT) and the satellite estimate (ARC) used for the insurance index. We believe this is because the merged product is heavily influenced by rain gauges that may or may not be operational in different years. Although the merged product is the most accurate product available, and extremely valuable for understanding what happens in any given year, the relative rainfall between years can change dramatically due to the introduction of a new weather station or the removal of a defunct one. Therefore, we believe our strategy of ranking years and comparing them is not well suited for this type of dataset. It is likely that more sophisticated statistical analysis would address this problem. Until that analysis is performed, our preferred use of the merged dataset as the most accurate indicator of the evolution of rainfall in a particular year.
- The alternative satellite rainfall product (TAMSAT) and merged product (ENACT) provide one avenue for validating the early window for rainfall, in case the vegetative products cannot be improved sufficiently to be useful and another alternative is not found. It is important to keep in mind that the effectiveness of the validation will be somewhat limited. Since all products include information from the same satellite to estimate rainfall, they may all be vulnerable to errors that are driven by the raw satellite observations.

4.3 Tuning the vegetative measure

The next step in the process was to focus on the best performing vegetative index, EVI. We completed some diagnostics and tests to check if the common sense assumptions we used for the vegetative index comparison could be changed to improve performance.

- Our strategy for vegetation remote sensing in index insurance was to interpret the landscape's response to rainfall (or lack of), so if there was plenty of rainfall then we might expect the landscape to appear greener, whereas if there was a dry spell then we would expect the landscape to appear more yellow or brown. However, this change would not happen immediately. To check the actual timing, we looked at different months before and after the rainfall event to see which window was most appropriate for the comparison between vegetation and rainfall estimate products. We looked at different windows to see if it actually took about a month for the landscape "greening" in response to rainfall. We checked the vegetation a month earlier, the month of, and one, two, and three months after the month of interest. **A lag of one month between the rainfall and vegetation index windows appears to be most appropriate in index design.**
- Next, we changed the area over which the vegetative data was averaged to see if it made a noticeable difference in the agreement between the vegetative and the rainfall products. We changed the size of the area averaged so that it was greater than the 10km x 10km of the rainfall region or less than the 10km x 10km area. **We found that the agreement did not change substantially, either for the early or late window.**

4.4 Validation of index using farmer recall, yield data, and farmer rain gauges

The R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) project focuses heavily on feedback from local experts, farmers in each village, and other data sources available. However, this information is not comprehensive because it is often obtained in response to particular issues, and not through a rigorous data capture/cleaning process. Therefore, care must be taken in its application. The most effective strategy is to utilize the information to identify issues for further follow up. It may be that the satellite validation process, which is developed automatically, compliments the client network information well. To understand how these two sources of information interact, we discuss validations based on farmer recall, available regional yield data, and farmer rain gauges. Figure 4.6 shows a farmer measuring rainfall from a rain gauge as part of the validation process for the R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) project.

- All of the data sources mentioned above are noisy and have important gaps in their coverage. Farmer rain gauges only have recent data, and therefore their use is more effective as a diagnostic for how the season has progressed in a specific location.
- In general, farmer recall and available historical regional yield data agree on the major drought years in the past decade or so, and are generally consistent with index payouts and vegetative sensing for major events across most of the region.
- The extent to which smaller, localized events can be accurately identified by the different data sources remains to be determined. As of now, it is unclear how smaller events can be targeted by a verified index insurance product.

Figure 4.6: Farmer in Geneti measuring rainfall for R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) project validation

4.5 Analysis of vegetation products using high resolution satellites and expert ground-truthing

Our approach in the use of satellites for checking indexes is to:

1. Check for disagreements between the satellite rainfall estimates (used for the index) and limited resolution satellites that regularly observe vegetation across all project areas.
2. Check the low resolution satellites that regularly observe vegetation using higher resolution satellites that do not have regular or comprehensive coverage.
3. Check all of the satellites and the assumptions behind the satellite verification process using targeted expensive satellite images and expert ground validation visits to a few strategic sites.

In this section we will work from the ground up, first describing the ground validations exercises (3), and then describing the use of satellites that have higher resolution but much less imagery to understand and check the satellites with satellites that regularly provide vegetation imagery (1 and 2).

There are a wide range of vegetation satellites, each with its own strengths and weaknesses. A central challenge for all of the satellite vegetation products is to figure out what the satellite is looking at. A satellite image is a complex mix of many things, often including shadows, bare soil, rocks, water, foliage from crops, foliage from grasses and trees, and other vegetation. Figure 4.7, is a typical example of farmland in the R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) project during August, the height of the cropping season. In interpreting the vegetative "greenness" of a satellite image of that area, it is important to keep in mind that the satellite product must work with this complex mix of covers.

Figure 4.7: Example of the many types of land cover in an agricultural area

Currently, a cutting edge research in satellite vegetation is understanding and addressing the mix of things that a satellite might be seeing. As a result, much of our work for this project has also been focused on better understanding what the satellites are seeing, and how to best work with the resulting imagery. Vegetation products that are calculated based on the assumption that a pixel is purely the crop being studied will be very vulnerable to this mix of ground cover and shadows. Therefore, instead of attempting to directly model agricultural production for a given pixel, we use vegetative images only to determine if the entire landscape has turned "brown" as an indicator of low rainfall.

The validation process of the vegetative imagery begins with a remote sensing expert on the ground, who visits a few places and verifies what is actually there. Although this method provides very accurate information, an expert can only visit a few places, at a few particular times of the year, therefore providing only a glimpse of what is actually on the ground. This type of validation is extremely expensive. We want to make sure the satellites would have identified famous droughts of the past. But we cannot use this source of information for droughts that have happened in the past, at times before the expert visited. Figures 4.8 and 4.9 illustrate an ongoing satellite expert ground validation exercises connected to this project (funded through separate NASA resources). In the latest visit (July 2013), an expert went to Adi Ha, Werkamba, Hade Alga, Mechare, Hadush Adi, and Abraha Atsbaha, and took 10-20 field records per village, including photos of the soil and pictures facing north, south, east and west. Figure 4.8 shows the locations of all the photographs taken in one of the villages, Hadush Adi. Figure 4.9 is one of the photographs taken there. Clearly these exercises can only be done for a small subset of locations (and times), which is why we are working to find ways we can use satellites and project feedback to reduce and target the number of expert visits.

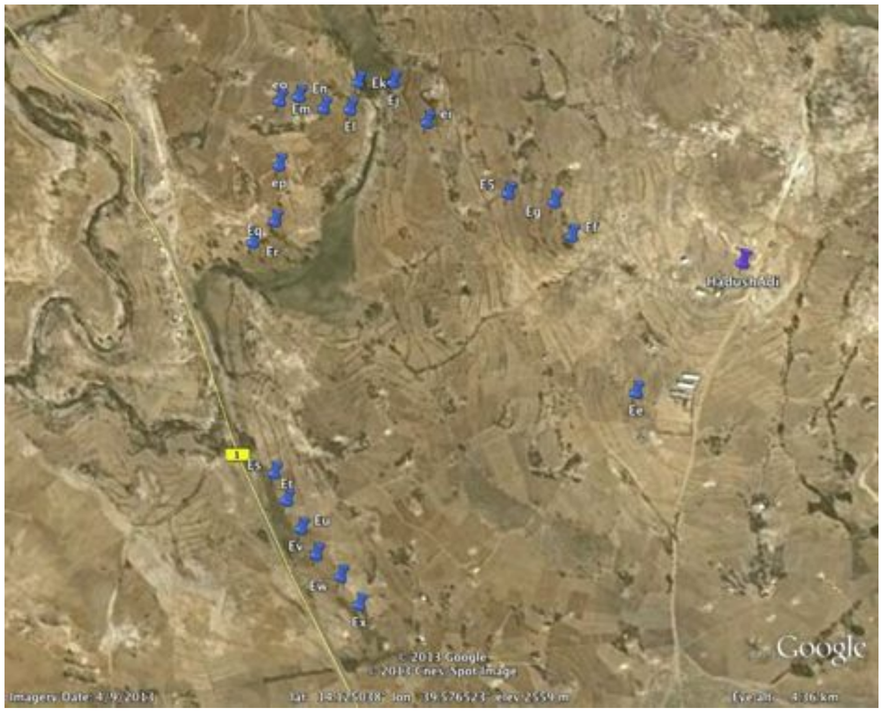

Figure 4.8: Locations of HadushAdi July 2013 Field Validation sites

We have performed a series of validations, where the most expensive and highest accuracy validations are used to check the less expensive information that is more widely available, covering the widest areas. Therefore, the use of the most expensive tools is reserved only for the places where issues have been identified. In order to perform these validations, we explored many different kinds of satellite imagery, each with its own strengths and limitations. Quickly outlined below are some of the satellite products that we have used in this study. We will define them and provide more detail later.

1. **Extremely high spatial resolution but only one or two very recent images.** (e.g., IKONOS and QuickBird). For these products, the pixels are so small (only a meter or so) that we can see individual houses and trees. This is as close as we can get to actually being on the ground. The biggest limitation with these satellites is very similar to the limitations we have with ground validation. We have only one or two images, and usually we do not have images from important historical droughts. If we only have one image available, we may not have images during droughts, and therefore we do not know what droughts look like. Alternately, we may only have an image during a drought, and therefore we do not know what "normal" looks like.
2. **Medium spatial resolution with one or two images per year for many years.** (e.g., Landsat TM). These satellites cannot distinguish individual trees and houses, but are relatively high resolution (e.g., 30m pixels) with a lot of detailed information. These satellites can provide one or two images per year over the span of decades. These images are rarely exactly at the time when crops need water, or exactly when a drought happens, but they allow us to understand what things have looked like in a detail for different years.
3. **Lower spatial resolution images over regular periods of time across all of Africa for several years** (e.g.,

Figure 4.9: Ground Validation Image, site E5. East-facing, showing fields of barley sown 48 days prior as well as a field of beans and a fallowing field in the distance.

MODIS and SPOT) The satellites that are most helpful for validation of rainfall are those that are very regularly capturing imagery of the vegetation across the entire project region. These have lower spatial resolution, (e.g., 250m x 250m), but cover all of Africa with good vegetation images every two weeks since 2000. We focus on MODIS because its imagery is easily available at no cost.

Figure 4.10 gives a sense for the difference in resolution of these different satellite products. In this set of satellite pictures of the Adi Ha village, the green square illustrates one 250m MODIS pixel, the fine imagery in the center is from high-resolution QuickBird, and the background is the 30m Landsat TM imagery. In order to get a sense for what things look like on the ground, Figure 4.11 shows a photo of the same landscape depicted in Figure 4.10. The irrigated orchard in the middle of the ground photo (Figure 4.11) corresponds to the green area at the top of the satellite image (Figure 4.10).

Our validation approach is to use the one available high resolution QuickBird image to better understand what we see in a given medium resolution Landsat TM pixel. Then we use the decades of sporadically timed Landsat TM imagery to understand what is in the lower resolution biweekly MODIS pixel. We use the MODIS pixel to identify specific droughts for validation of the insurance index. Although the MODIS pixel appeared small in Figure 4.5, by looking at the QuickBird and Landsat TM imagery in Figure 4.10, it becomes clear that there are many different land covers within a MODIS pixel. A MODIS pixel covers more than 6 hectares, so it can often stretch across many fields, trees and other land uses in smallholder agricultural areas. For example, as you can see in Figure 4.10, areas near the river are greener than those further away. The green area in the upper left corner of the MODIS pixel is the irrigated region.

The question remains: **How can we use satellites like MODIS if we do not know what is inside of the MODIS pixels?** We can combine information from each of these different kinds of satellites, using the detailed imagery that is only available once or twice in history to identify problems and understand what the bi-weekly but less detailed imagery represents. Satellite experts validate the satellites with strategic ground visits. This information is used to compliment the available ground measurements and the experiences reported by farmers and local experts.

We did several analyses to compare the relationship between the different kinds of satellites, to see if the land coverage identified in the high resolution QuickBird and IKONOS imagery agreed with the medium resolution Landsat TM imagery and the lower resolution MODIS pixel. For QuickBird, IKONOS, and Landsat TM, it is feasible to perform analysis that determines the *vegetative fraction* in each pixel. The vegetative fraction is the percent of the pixel that is covered by leafy foliage, as opposed to shadows, bare soil, water, or other things. Our general findings were quite encouraging, providing some explanation for the performance of the MODIS EVI in rankings.

- Vegetative fraction was consistent across the different resolutions of all of the satellites. Therefore, for the regions studied, **using fine imagery we have verified that the coarser resolution satellites are effective in**

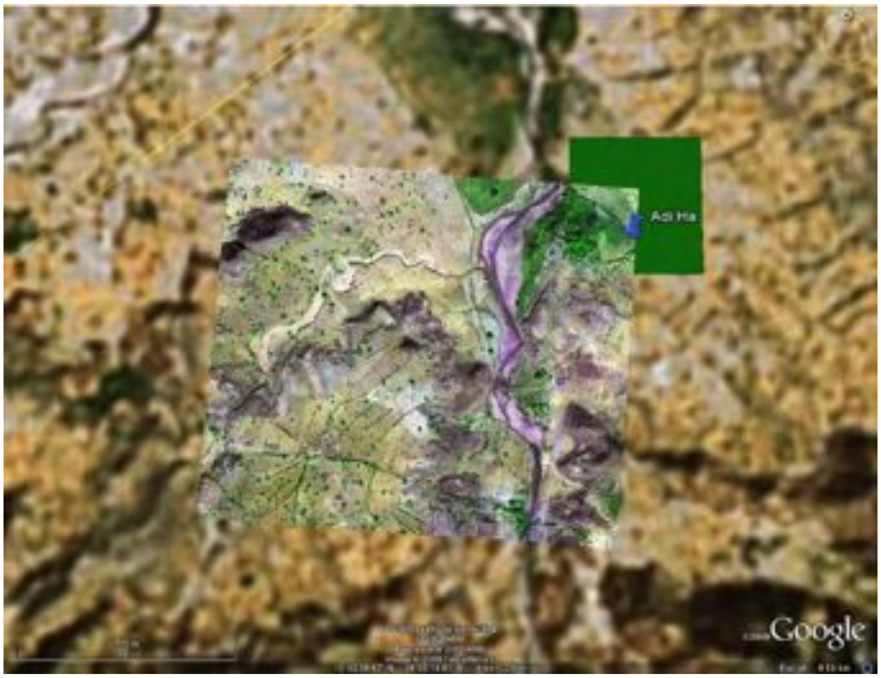

Figure 4.10: Example of QuickBird, Landsat TM, and MODIS imagery in Adi Ha

Figure 4.11: Adi Ha view from ground, looking towards irrigated orchard

representing vegetative fraction.

- **EVI could be aggregated from fine scales to coarse scales.** This is an important validation because we aggregate EVI over space for our ranking comparisons.
- EVI estimates were very similar (very highly correlated) to vegetative fraction. That means that for this area, **we can interpret EVI as representing the fraction of area covered by vegetation.**
- **These findings explain part of why EVI performed well in our initial investigations.** They are consistent with global studies performed by some of our collaborating satellite researchers, validating their applicability in the specific R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) region [Small2013]. These studies also found that older products such as NDVI did not have as close relationship to vegetative fraction or scalability as EVI.
- **It may be possible to improve our use of EVI through knowledge of the vegetation fraction within each pixel.** Although our quick diagnostics did not find immediate improvements, it is possible that with more work we will eventually lead to better understanding of droughts by paying more attention to pixels that have more vegetation than those with mostly bare earth.

4.6 Assessment of index and validation process using the experience of the 2012 drought

The R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) project has been active since 2009. The first large scale drought while the index insurance project was in place occurred in 2012. In October and November of 2012, satellite data triggered payouts to more than 12,000 farms in Ethiopia. This type of index insurance project and the scaling up process were put to the largest test to date when $322,772 in payouts were issued to farmers. This drought was particularly relevant to our validation analysis because of the variations in the regional severity of the drought across the R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) sites. Some farmers, located in less severely impacted locations, were awarded partial payouts, while many, in the most badly affected areas, received full payouts.

The 2012 drought enabled us to see if the insurance provided the appropriate payouts in the appropriate regions. **If the satellite validation techniques we are exploring in this project were able to identify the places where the index did not perform well in 2012, then there is potential that the validation techniques might be effective.**

In general, the end-of-season project assessment suggested that overall the 2012 indexes effectively represented the local experiences during the growing season, and the contracts performed well for the vast majority of farmers. The payouts appear to match where the drought hit hardest, and the timing of the payouts appears to reflect the timing of the drought.

For the first part of the 2012 agricultural season, the rainfall amount was fairly typical in most places, close to average. Many tabias experienced substantially above average rainfall and only a few tabias experienced rainfall deficits that were as low as the one in four or worse event. However, there was a meaningful, relatively widespread rainfall deficit near the end of the rainy season, when crops were likely to be flowering and in need of rainfall. This deficit coincided with ground-based rainfall measurements and reports from the field. For example, in the Ethiopian NMA ENACT data averaged across Tigray (Figure 4.12), which is based on ground measurements of rainfall augmented by satellite data, there is a large negative anomaly in late August [EthiopiaNMA]. Looking at another figure from the Ethiopia NMA maproom, plot b of Figure 4.13, it is clear that the dry period was the largest of the three years shown.

However, the rainfall average across Tigray shown in Figure 4.13 tells only part of the story. The 2012 experience varied substantially across Tigray. For the entire set of indexes, this is an event that is about the worst year out of three or four, however, for many villages, it is substantially worse.

Out of the 76 villages purchasing insurance in 2012, the IRI has received complaints from about eleven villages. Following up on the complaints, most were found to concern minor logistical or communication issues. Upon investigation, three complaints merited more meaningful follow up actions. Working with project partners, the IRI team

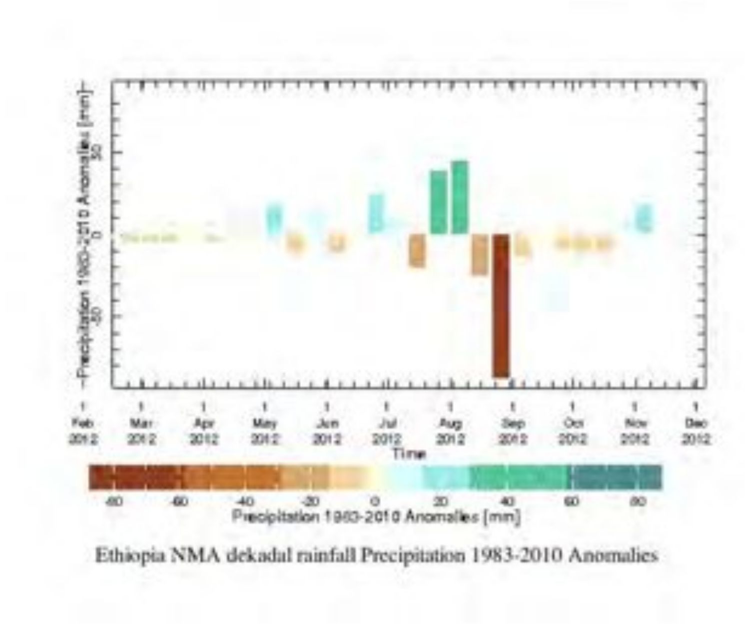

Figure 4.12: Ethiopian NMA ENACT data averaged across Tigray

visited several project villages in the eastern highland districts of Kinte Awelo and Saesi Tsaedaemba, in the western midland district of Kola Tembien as well as in the lowland districts of Tanqua Abergele in the south-west and Raya Azebo in the south.

Two of the villages that expressed concerns were in the southern region of Raya Azebo (Hawelti and Tsigea). The farmers from these villages were concerned about the size of the payouts, which were relatively low. The team visited these villages to understand how much their experience differed from their neighbors with larger payouts. The discussion with the design team in Hawelti is shown on the left side of Figure 4.14 and the rain gauge in Hawelti is shown on the right side. Figure 4.15 is a photo of rainfall early in August for that site. The location of the meeting and rain gauge can be seen in the Google Earth rendering of Figure 4.15. By comparing the two figures, it is possible to get a sense of the location of the rain gauge and meeting in the photo of early season rainfall. These images serve as an example of on the ground network for verification, which includes consulting with local experts, farmers, communities and rain gauges.

The follow-up revealed that the concerns were not primarily the result of error in satellite rainfall estimation, but instead the differences in the insurance packages offered between these villages and the neighboring villages. The villages that expressed a concern were only offered the very low cost, low payout, high deductible version of the insurance, while other villages in the region were offered an option of a higher payout, lower deductible version of the insurance. If the farmers in Hawelti and Tsegea had purchased the dry insurance option, they would have had much higher payouts in 2012. However, there was some scope for index improvement as well. In the design team discussions, adjustments in the timing of the windows for the indexes were suggested. These differences in the timing of the windows for the indexes would have increased payouts in 2012, and would have been more similar to neighboring villages.

The third village that expressed a concern, which merited a detailed follow up, was Imba Rufael, in the Tanqua Abergele district. In Imba Rufael, there was a small payout. Initial reports indicated that farmers in this village and surrounding areas expected to receive a larger payout. Follow-up discussions with farmers indicated that although they felt that the year was not one of their most severe years, the rainfall was still not sufficient and a meaningful payout was merited. Figure 4.16 (left) was taken during the visit to follow up on farmer complaints in Imba Rufael. **It was evident from the follow up that it was necessary to improve the index in Tanqua Abergele.**

In parallel to the village visits, the satellite sensing experts identified the R4 Rural Resilience/Horn of Africa Risk

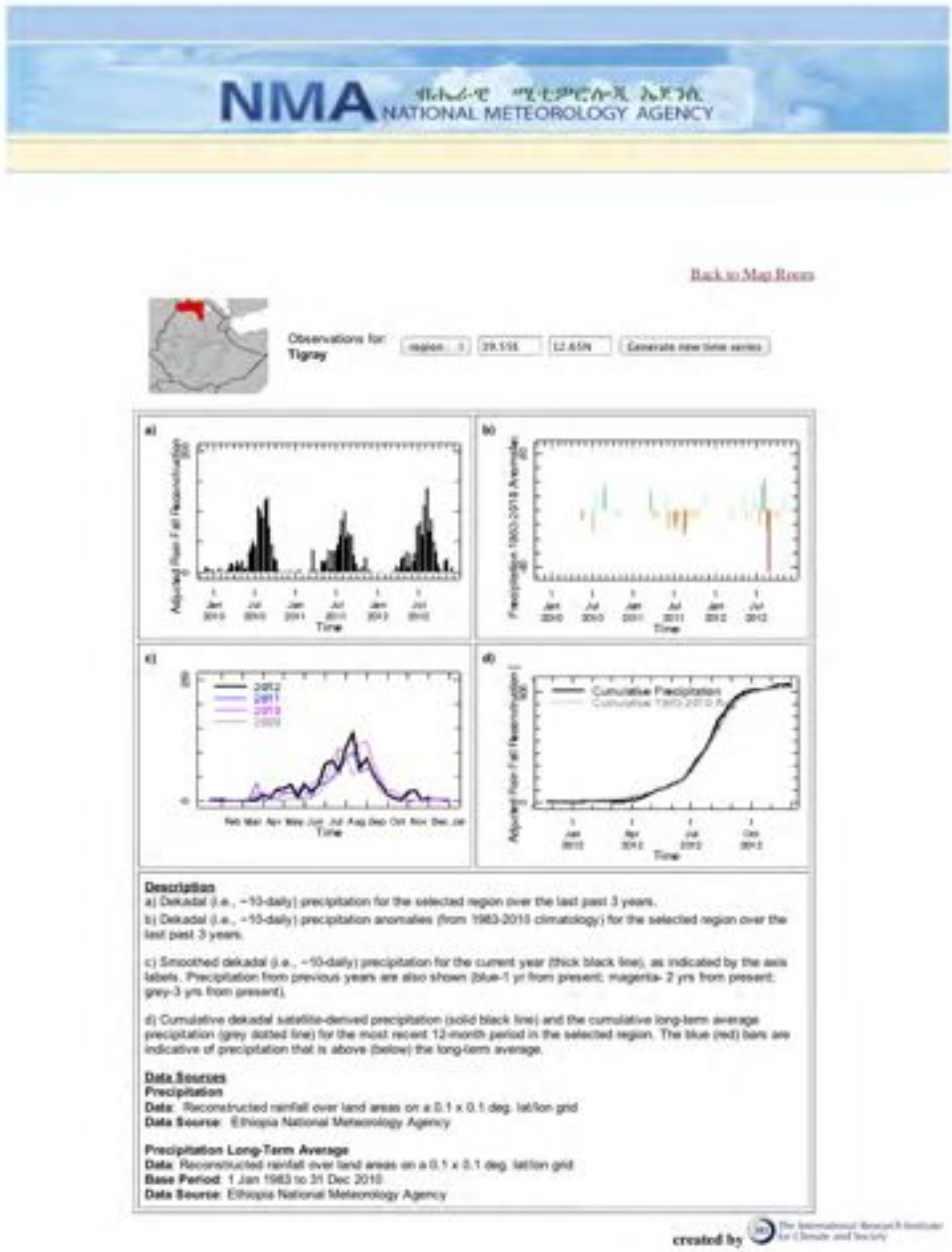

Figure 4.13: Ethiopia National Meteorology Agency maproom

Figure 4.14: Design team in Hawelti discussing concerns about 2012 experience (left) and a rain gauge at site of Hawelti design team meeting (right)

Figure 4.15: Photo of rain in Raya (near Hawelti) on August 3, 2012 (left) and Google Earth rendering of view of Hawelti (right), the pin marks site of design team meeting and rain gauge

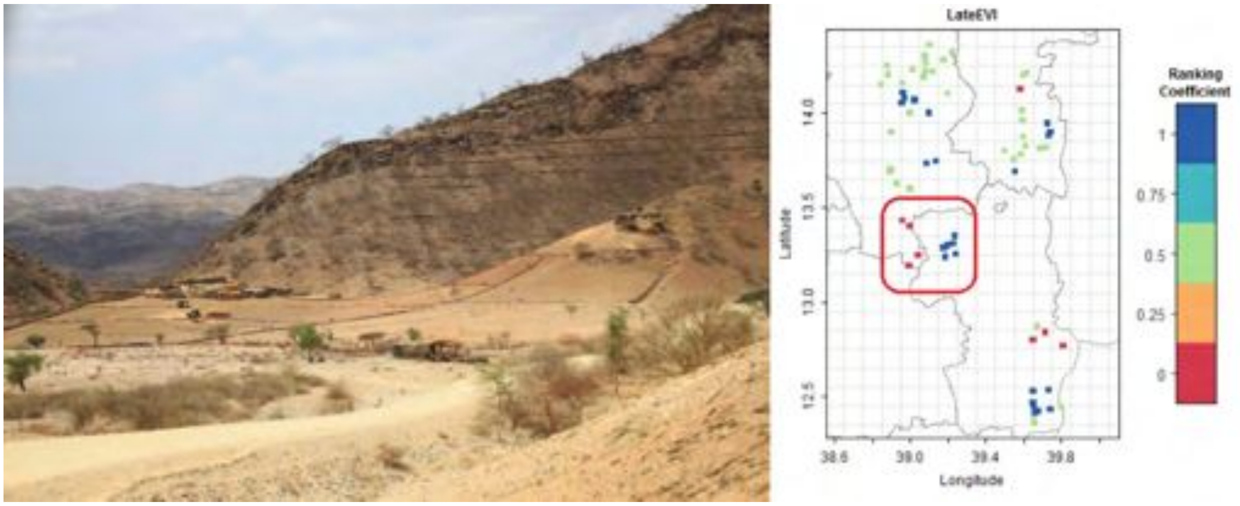

Figure 4.16: Photo of Tanqua Abergele taken during visit to follow up on farmer complaints (left) and the ranking agreement for EVI compared to the ARC R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) index for the late season (right). A rank of 1 means that both the vegetation index captures 100% of the "bad years" measured by the ARC index. A rank of 0 means that the vegetation index captures none of the bad years.

Transfer for Adaptation (HARITA) sites that had the lowest level of agreement between EVI and the satellite rainfall index. Figure 4.16 (right) summarizes the level of agreement. In the figure, we show the late season because the vegetation indexes have a higher skill in the late season compared to the early season. **All of the sites with meaningful complaints in 2012 are included in the small number of villages tagged as red points (worst agreement) in the LateEVI plot.** As can be seen by comparing with Figure 4.17, Tanque Abergele are the red points on the West side of the red box (discussed further below), and Tsegea and Hawelti are in the group of three red points to the Southeast of the red box.

The woredas (regions) of Tanqua Abergele and Samre lie next to each other in the southwest of the R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) zone (depicted by the red box in Figure 4.18). These two figures show the relationship between EVI and the satellite rainfall index in this region. The Tanque Abergele region villages, which complained, shows up clearly as an area with complete disagreement between EVI and ARC rainfall, but in Samre, where farmers did not complain, there was complete agreement. Since the two woredas were so close to each other, the dramatic differences in levels of agreement between the nearby villages were a sign to the remote sensing experts that further follow up was appropriate for the area (see Figure 4.18). **The lack of agreement between the regions, identified by the remote sensing experts and through ground-based project discussions in 2012, suggests (albeit qualitatively) that the EVI ranking technique has great potential as a validation tool for the late window, one that might be able to preemptively flag issues before a product is brought to market.**

The other sources of information such as historical yield assessments or the farmer interviews of 2010-2011 did not clearly identify concerns for those regions. Of course, the sources of information available during the product design were used to flag and improve indexes at any sites where problems were uncovered, so any issues reflected in these sources of data should have already been addressed before insurance sales started.

After the field visit in Imba Rufael, the windows were changed to better reflect farmer experiences. When those new windows were included through the ranking analysis, *the relationship improved* for the late season. This outcome should not be taken with too much optimism–given our current level of understanding of what the vegetative sensing represents, we do not have a definitive mechanism for why changing the window timing should lead to improved agreement between the index and the vegetative imagery.

Figure 4.17: Map of R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) sites in 2012.

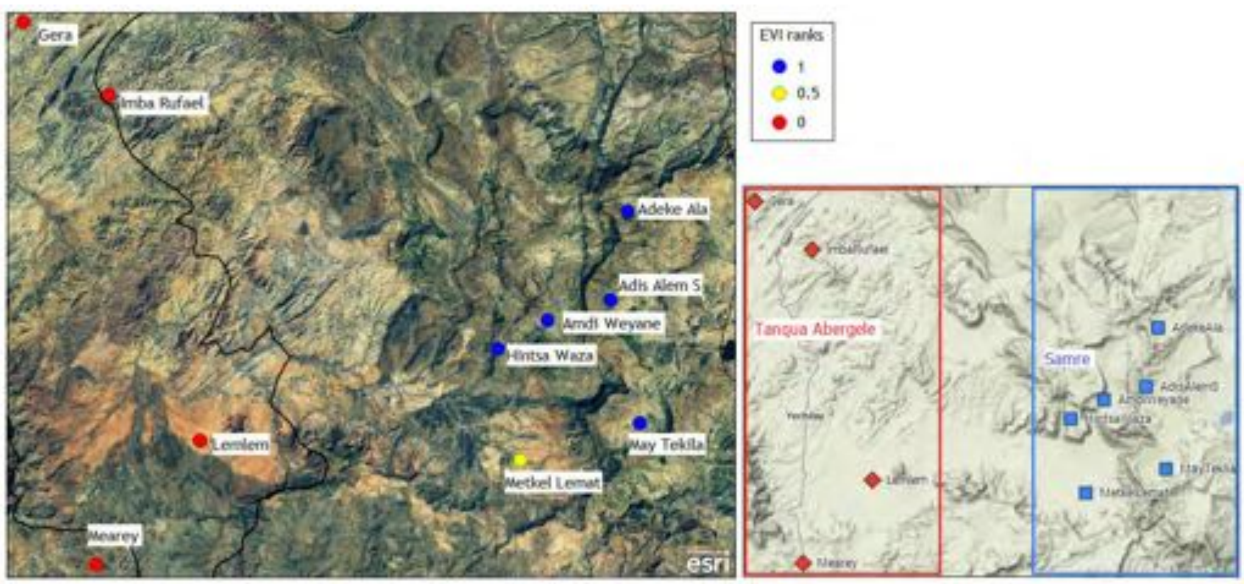

Figure 4.18: Case Study Map. Sites in the Tanqua Abergele and Samre woredas and the ranking statistic. 1 (blue) means complete agreement between ARC rainfall bad years and EVI vegetation bad years, 0 (red) means complete disagreement.

CHAPTER

FIVE

ADDITIONAL DETAILS

5.1 Details: Background

In this chapter we elaborate on many of the points introduced in the previous chapter, providing background, details and supporting analyses not presented earlier.

5.2 Details: Comparison of range of satellite vegetation, rainfall estimate, and merged datasets

5.2.1 Satellite products

There are many types of satellite-derived products available, each with their own strengths and weaknesses. Here we have focused on two particular types: satellite rainfall estimates and estimates of vegetative health.

There are several satellite rainfall products, each using a different formulas to link clouds to rainfall. For more details on satellite rainfall, see [Greatrex2013]. The satellite rainfall estimates presented in this report work by taking infrared images of cloud tops, a proxy for cloud top temperature and height. Across the tropics, where most rainfall comes from towering thunderstorms, the cloud top temperature can then be used to infer whether the cloud is raining or not. This is shown in Figure 5.1.

Vegetation estimates are created by carefully measuring the wavelengths and intensity of visible and near-infrared light reflected by the land surface back up into space. An algorithm called a "Vegetation Index" is then applied to quantify the concentrations of green leaf vegetation around the globe. There are several different types of vegetation indexes, which can be used, each monitoring a different aspect of vegetative health. Because there are several global satellite products, the challenge is not to find a product that could potentially be applied as an index for insurance–instead the challenge is to develop an index that is verified in each place and effective at addressing important hazards that farmers in each specific location actually face.

The specific products discussed in detail in this report are shown below in Table *Remote Sensing Products Used for Initial Analysis*. These products are freely available online, on IRI's Data Library website: http://iridl.ldeo.columbia.edu/. Some of them, such as TAMSAT and Ethiopia NMA are available on their own websites provided below.

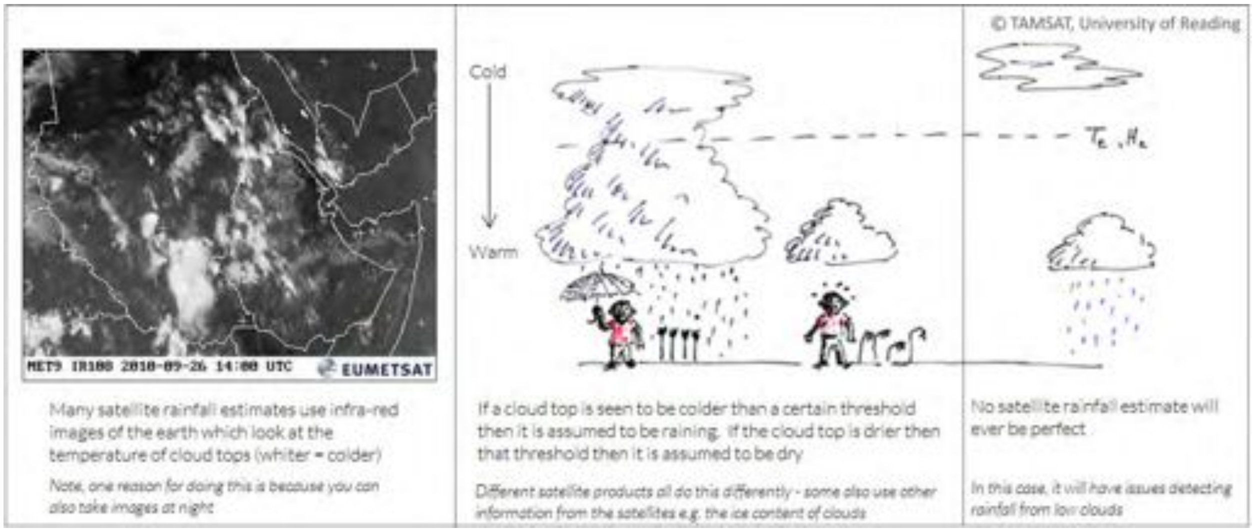

Figure 5.1: An explanation of satellite rainfall products. Some, including NOAA ARC2 used in R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) project, also use microwave images to gain additional information about rainfall.

Table 5.1: Remote Sensing Products Used for Initial Analysis

Working Name of Index	Type of Remote Sensing	Full Name of Index	Name of Producer	How often it provides measurements	Resolution (spatial extent) of measurement*
ARC (ARC2) [ARC]	Rainfall	African Rainfall Climatology	NOAA-CPC	Daily	10km
TAMSAT [TAMSAT]	Rainfall	Tropical Applications of Meteorology using SATellite data and ground-based observations	University of Reading, UK	10 days	4km
ENACT [EthiopiaNMA]	Satellite rainfall blended with ground-based rainfall measurements	Enhanced Climatology Time Series	Ethiopian NMA	10 days	10km
EVI [EVI]	Vegetation	Enhanced Vegetation Index computed from the MODerate Resolution Imaging Spectroradiometer on-board TERRA satellite	NASA	16 day composite	250m
NDWI [NDWI]	Vegetation's water content	Normalized Difference Wetness Index computed from the MODerate Resolution Imaging Spectroradiometer on-board TERRA satellite	NASA	16 day composite	250m

5.2.2 Our comparison process

We order the years from 2000 to 2012 from best to worst for the satellite rainfall estimate, with the least rainfall being the worst. We then rank the years from 2000 to 2012 for a satellite vegetative index with the least "green" being the worst. We then count the number of years ranked in the worst four (the worst third of the years) and use that as the diagnostic to reflect the level of agreement between "bad years." In the tables, the count is divided by the number of years, so if 2 years are identified as being in the worst 4 for both datasets, we would report "0.5."

Correlation, a valuable and often used metric, may miss many important things that can go wrong in insurance, so we do not use correlation as the primary metric for our report. Insurance does not provide payouts in good, or average years, so payout correlation calculations are driven by a relatively small set of bad events. Correlation is determined by large events that agree, so a single large payout in one very severe year can lead to very high correlations, even if the insurance misses most of the years that farmers would need payouts.

The ranking metric we use typically does represent high correlations, while at the same time more directly targeting the problems that cause concern in insurance programs. If an insurance product has payouts in two of the 3 worst years in the past ten, it is very likely that the correlation will be high. There are other correlation measures, such as rank correlation directly rate the agreement of ranking between datasets. We do not rely on rank correlation either, because the good, or normal years is not particularly valuable in index insurance, which can only target bad years, but we are actively considering additional metrics that might be more appropriate than the ranking measure presented here.

Using several strands of evidence is particularly important for drought because it is a complex phenomenon. When all products select the same drought years, their agreement suggests that those years were objectively the worst. So, in areas with strong agreement between vegetation data and rainfall data, our confidence in the contracts paying out in the worst seasons is strengthened. In locations with ground-based data from rain gauges or from farmer interviews, the performance can be further checked using the same approach.

It is important to note that a perfect agreement between any two products is not possible. Science is not magic. There will always be some level of error in any product. Crop response to rainfall is far from uniform across the range of crops farmers grow, and the actual water available for crops is also driven by factors such as topography and soil porosity. In our study, we hope that regions of high agreement are regions where the satellite rainfall derived R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) index is performing as expected, while regions with high disagreement are places where further ground-truthing might be necessary.

5.2.3 Detailed presentation of comparison results

Figure 5.2 shows the level of agreement between the vegetative products and the ARC rainfall estimate for both the beginning and end of the season. By looking at the bottom 3 panels in the figure compared to the top 3 ones, it is easy to see that late season EVI is the vegetation index with the highest level of agreement with ARC. The R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) Tanque Abergele case study region, mentioned earlier in this report, is marked as a red box in the figure.

Below we will present some summary tables (Table *Early season average agreement between satellite products and ARC by woreda for the 12-year period* and Table *Late season average agreement between satellite products and ARC by woreda for the 12-year period between 2000-2012*) of the level of agreement between the ARC index and several satellite rainfall estimates and vegetative indexes. Because NDVI was less preferable based on its known errors as well as our initial agreement checks, we do not present it in the tables below, to help focus our presentation.

Table *Average Satellite Ranking for the 12-year period 2000-2012 across all 83 project villages* provides the ranks of the different products across the entire project region. Looking at this table, one can see that vegetation satellite products (EVI, NDWI) did not match as well at the beginning of the rainy season. Both EVI and NDWI products agree better with ARC in the late season (average agreement across all sites: EVI = 0.57, NDWI = 0.45) than in the early season (average agreement across all sites: EVI = 0.35 and NDWI = 0.422). In particular, the performance of EVI suggests that it was the most promising vegetation satellite product for ARC validation and may be useful in helping to scale index insurance projects.

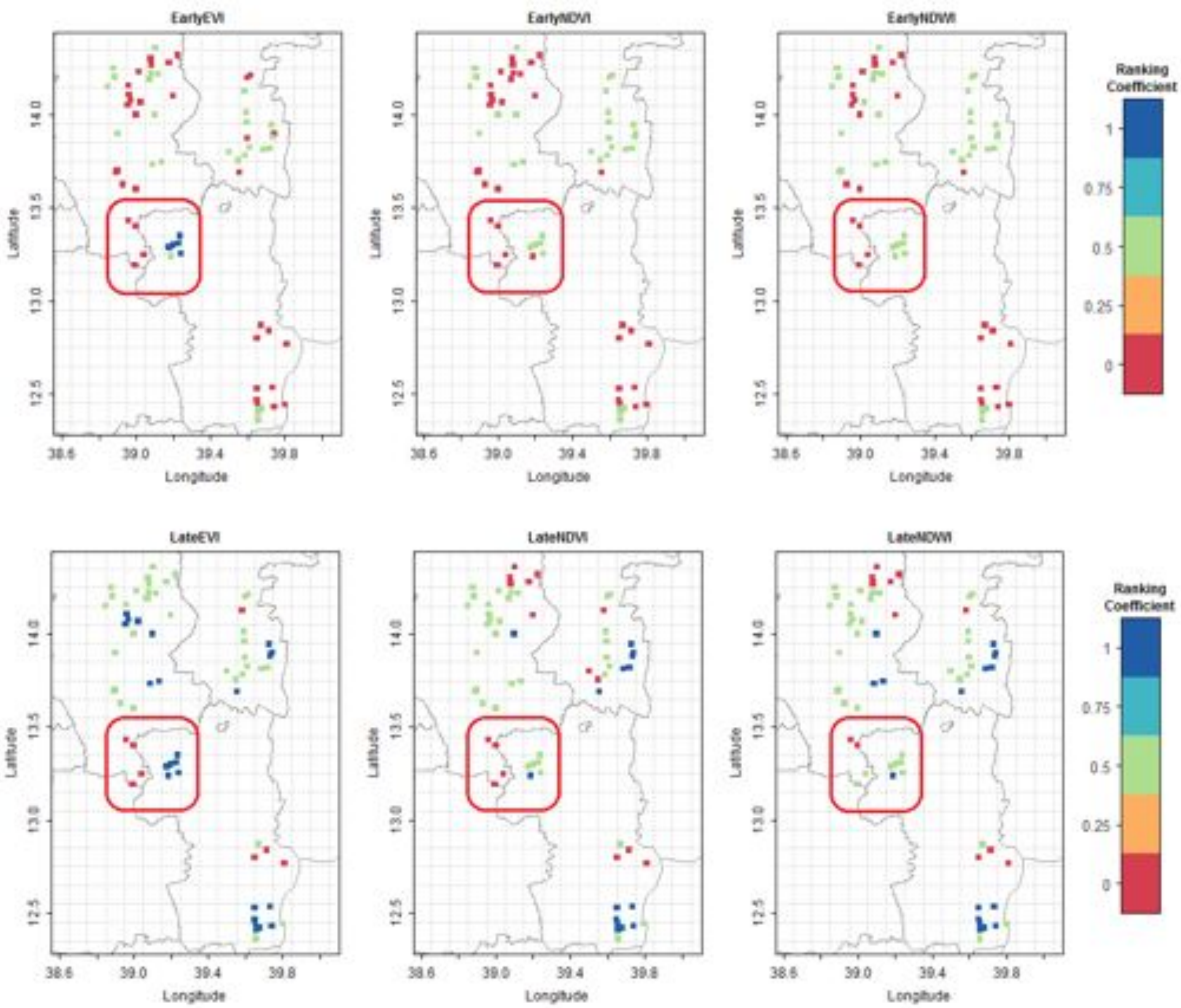

Figure 5.2: The ranking agreement for three vegetation indexes (NDVI, NDWI and EVI) compared to the ARC R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) index. The top row shows the early season and the bottom row shows the late season. A rank of 1 means that both the vegetation index captures 100% of the "bad years" measured by the ARC index. A rank of 0 means that the vegetation index includes none of the worst years seen by the rainfall index.

These results indicate that the early season is more challenging for vegetation sensing. Since vegetation products are designed to reflect the health of existing vegetation, it is not surprising that they do not perform as well at the beginning of the rainy season, when crops are not yet fully established.

Table *Early season average agreement between satellite products and ARC by woreda for the 12-year period* presents the level of agreement at the beginning of the season and Table *Late season average agreement between satellite products and ARC by woreda for the 12-year period between 2000-2012* presents agreement at the end of the season, averaged across Woredas. Note that since ARC must by definition agree with itself, its agreement level is reported as 1.

Table 5.2: Average Satellite Ranking for the 12-year period 2000-2012 across all 83 project villages

Satellite Product	Type of Product	Early Season	Late Season
ARC	Rainfall	1	1
TAMSAT	Rainfall	0.625	0.68
ENACT	Rainfall	0.611	0.45
EVI	Vegetation	0.35	0.57
NDWI	Vegetation	0.422	0.45

Table 5.3: Early season average agreement between satellite products and ARC by woreda for the 12-year period

Region	Woreda	ARC	TAMSAT	ENACT	EVI	NDWI
		Rainfall Product	Rainfall Product	Rainfall Product	Vegetation Product	Vegetation Product
Eastern Highlands	Atsbi	1	0.75	0.85	0.65	0.6
Eastern Highlands	KinteAwelo	1	0.58	0.63	0.31	0.38
Eastern Highlands	SaesiT-saedaemba	1	0.58	0.66	0.44	0.41
Midlands	Adwa	1	0.82	0.5	0.09	0.34
Midlands	Ahferom	1	0.38	0.55	0.38	0.44
Midlands	KolaTembien	1	0.46	0.54	0.32	0.39
Midlands	WiereLahe	1	0.75	0.75	0.29	0.54
Lowlands	Samre	1	0.75	0.75	0.75	0.71
Lowlands	Tan-quaAbergele	1	0.5	0.5	0.42	0.42
Lowlands	Alamata	1	0.5	0.5	0.25	0.42
Lowlands	RayaAzebo	1	0.63	0.53	0.18	0.15

Table 5.4: Late season average agreement between satellite products and ARC by woreda for the 12-year period between 2000-2012

Region	Woreda	ARC	TAMSAT	ENACT	EVI	NDWI
		Rainfall Product	Rainfall Product	Rainfall Product	Vegetation Product	Vegetation Product
Eastern Highlands	Atsbi	1	0.75	0.38	0.75	0.5
Eastern Highlands	KinteAwelo	1	0.56	0.43	0.75	0.5
Eastern Highlands	SaesiT-saedaemba	1	0.58	0.46	0.56	0.41
Midlands	Adwa	1	0.75	0.5	0.59	0.34
Midlands	Ahferom	1	0.75	0.5	0.5	0.34
Midlands	KolaTembien	1	0.83	0.61	0.44	0.33
Midlands	WiereLahe	1	0.58	0.36	0.54	0.46
Lowlands	Samre	1	0.5	0.54	0.71	0.71
Lowlands	Tan-quaAbergele	1	0.56	0.69	0.19	0.44
Lowlands	Alamata	1	0.75	0.25	0.75	0.5
Lowlands	RayaAzebo	1	0.78	0.33	0.58	0.53

Detailed comparisons across villages for specific years revealed that **it was more challenging for EVI vegetation satellite product to detect drought during the less extreme years.** The EVI satellite vegetation product was found to be more skillful at picking out extremely dry years (e.g., the type of years that would trigger a large payout), compared to less extreme ones, which might trigger small payments. We will discuss this further in our discussion of the 2012 experience.

Other rainfall satellite products (TAMSAT and ENACT) also showed promise as tools for evaluating the performance of the ARC rainfall product.

Specifically, TAMSAT had the best correspondence with the ARC satellite product - about 60% match in both the early and late season. However, all of the rainfall estimates presented here are based on a similar methodology, and it is reasonable to expect that the estimates might be subject to similar biases or errors. This means that other rainfall estimates cannot be relied on exclusively for validation.

Because the ARC2, TAMSAT and ENACT datasets all have histories that go back 30 years, we did a ranking comparison of only those sources, checking for the level of agreement between the lowest ten years in each dataset, averaging across the sites. For the Early window, we found an average agreement of 5.8 years out of ten for the merged dataset and ARC2, and 5.9 years for the TAMSAT dataset. For the late season, we found an average of 4.7 years for the merged dataset and 6.7 for TAMSAT.

There are also some very old NDVI products (AVHRR). Because there are challenges with the uniformity for comparisons across years between different satellites (and because these satellites are no longer active), we do not present our analysis of these datasets. Given the caveat that there are problems with comparability across different satellites over the years, these old products performed similarly to the other NDVI products we explored.

5.3 Details: Tuning the vegetative measure

5.3.1 Delay between rainfall and vegetation timing

Our strategy for vegetation remote sensing in index insurance was to interpret the landscape's response to rainfall (or lack of), so if there was plenty of rainfall then we might expect the landscape to appear greener, whereas if there was a dry spell then we would expect the landscape to appear more yellow or brown. However, this change does not happen immediately. As anyone who has kept a garden knows, plants take some time to respond to rainfall and it can often take a landscape several weeks to change color.

One of the assumptions that the IRI has made in prior work is that this "lag time" between the rainfall and the response of the landscape is often about one month. Until now, we have not checked the exact time-scale for index insurance in the R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) project. To test this, we calculated the ranking coefficient between the ARC rainfall index and versions of the EVI vegetation product with windows lagged at different intervals. For example, if the ARC R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) window was from the 1-30th April, then a lag of +1 month would mean comparing to an EVI window of 1-31st May. As the plot in Figure 5.3 plot shows, the pattern of lagged correlation values is consistent across all sites: positive, but low values for a lag length of zero months, peak agreement occurs at a 1-month lag, and values decreasing in time for the two and three month lags. **The highest levels of agreement were found for our original one month delay between the vegetation and the midpoint of the rainfall window.**

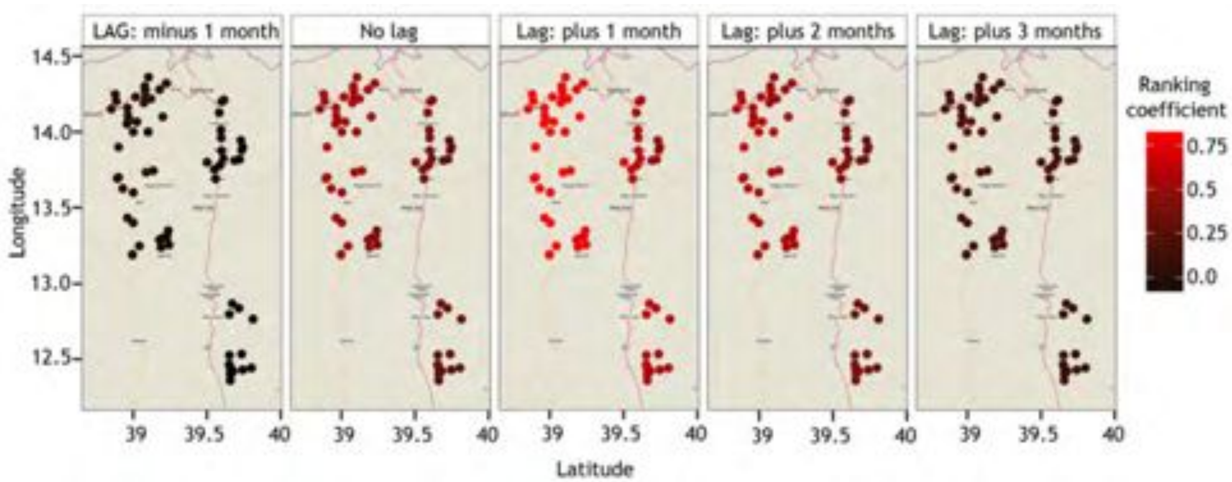

Figure 5.3: An investigation into the most appropriate lag time between the rainfall and vegetation data. The best relationship between the two variables appears to be when there is a lag of one month.

5.3.2 Size of area averaged for vegetation index

As we have described earlier, and as Figure 5.4 illustrates, there are many MODIS EVI pixels inside every ARC rainfall pixel. Our default, common sense based initial step has been to average all the MODIS pixels inside each ARC pixel as shown in the top drawing in Figure 5.5.

In this step of the analysis (Figure 5.5), we varied the number of EVI pixels used inside the ARC pixel to identify what effects this had on agreement levels. Specifically, in Case 1, we wanted to see how the results will change if we reduce the number of EVI pixels we used in the analysis. In Case 2, we wanted to see if the results were better when the EVI pixels were centered on the village of interest rather than on the center of the ARC pixel (Figure 5.5). In Case 3, we included more EVI pixels in the analysis in order to try and capture the large scale picture. On one hand, a larger EVI averaging area improves the error cancellation across a greater number of pixels and gives an indication of the large scale picture. On the other hand, expanding our averaging area increases the chance of including non-relevant pixels into our analysis.

Interestingly, although there are scattered sites with better or worse performance, there appears to be no clear impact of changing the size of the averaging box. This is likely to be because of two reasons: firstly we are comparing against ARC data rather than farmer experience, so you might expect choosing identical pixels to the ARC one to work best. Secondly, we might be either incorporating too much local variability or too many non-vegetation pixels for the approach to work well. The results for the early and late season are summarized in Figure 5.6.

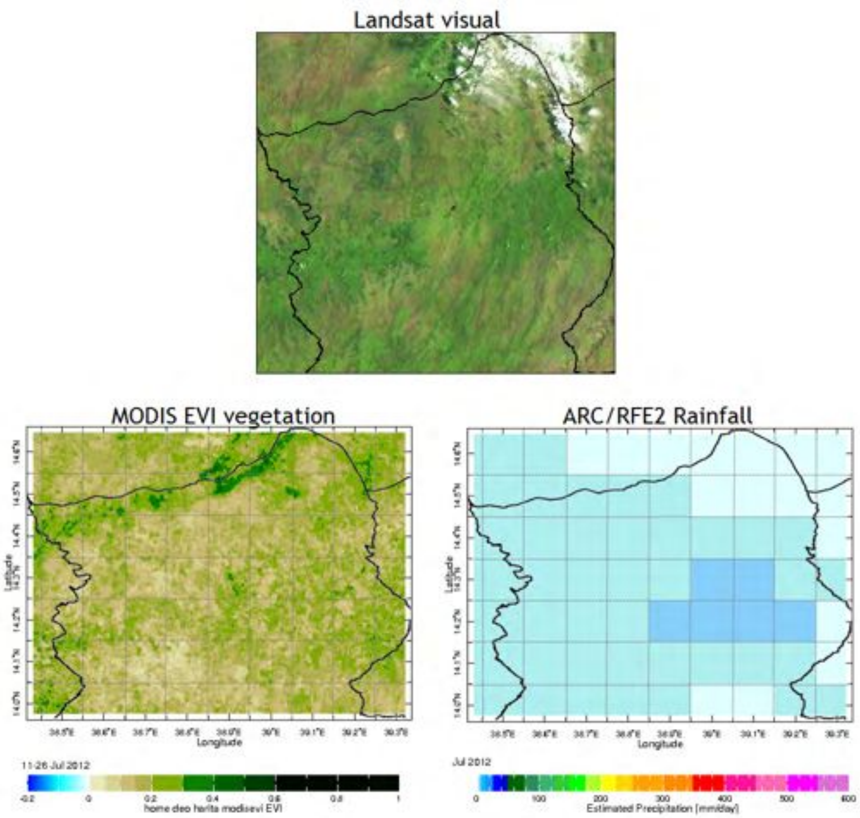

Figure 5.4: Example output from Landsat TM visual imagery (resolution 30m), MODIS EVI (resolution 250m) and ARC rainfall (resolution 10,000m).

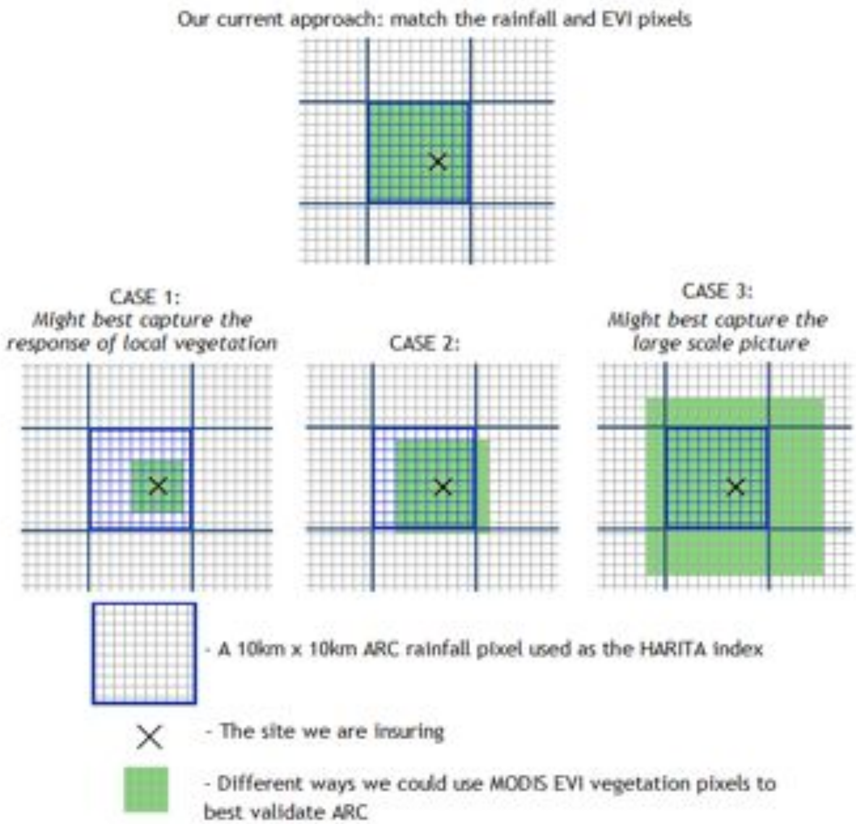

Figure 5.5: A schematic to show our different approaches to the EVI averaging area

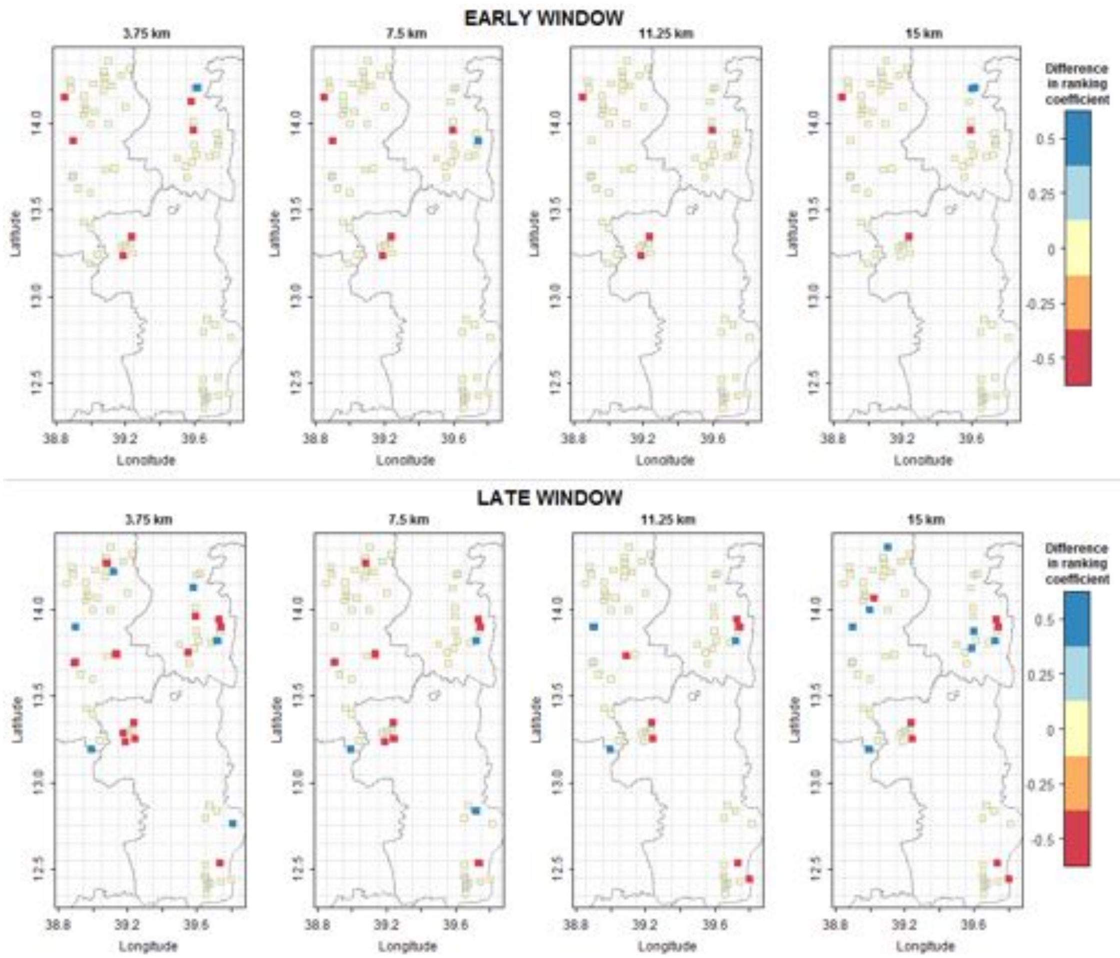

Figure 5.6: This shows whether using a different EVI averaging box affects the relationship with rainfall. A value of 1 means that the relationship gets much better and a value of 0 suggests that it gets much worse.

However, this basic analysis allows us to pose a new question. So far in the case studies and initial results, we have seen promising signs to suggest that EVI can identify locations where the ARC window was calibrated incorrectly. Now, it is possible to test whether we can use a box centered on a site to identify regions where the satellite pixel is not capturing the rainfall over the site. One example might be where insured site is right at the edge of satellite pixel and because of topography etc., we may not be capturing the correct rainfall patterns. You would not expect such a situation to occur very often across the 83 sites, but a way to move forwards from this analysis would be to study those locations which consistently showed a better (or worse) performance as the averaging box changed and check how the insured site compares to the ARC rainfall pixel. If the R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) project scaled up to cover many thousands of villages then this type of exercise might then be useful in quickly identifying locations that need additional groundwork or study.

5.4 Details: Validation of index using farmer recall, yield data, and farmer rain gauges

In the earlier discussions we have mentioned that farmer recall, yield data, and farmer rain gauges have been utilized in the project. Here we will elaborate a little more on these data sources and how they are used in the project.

5.4.1 Quantitative farmer discussions about seasonal timing and historical bad years

One source of information used in the product design, was the farmer recollection of bad years in each village. In the fall of 2010, local partners utilized the village design team discussion process we had established for the initial 5 villages, and applied that process in about eighty new villages. As part of the process, farmers were asked to list the 5 worst drought years in their village. That information was tabulated and used in the design scripts and two diagnostics were calculated. Although these two diagnostics were based on the basic philosophy of the matching of bad years, they were calculated slightly differently because we expected that the farmer list would not include all bad years. Farmers could not remember all bad years, especially ones that happened a very long time ago. Also, since we want to use the 2010 interviews post 2010, we need to have a metric that did not penalize an index for bad years that occurred after 2010. In general, because comprehensive farmer interviews for all villages takes meaningful effort and expense, it is valuable to have metrics that are effective for interviews performed in previous years.

As shown in Table *Index Agreement with bad years reported by farmer groups in each village in 2010*, the first diagnostic, TOK, is the number of bad years during which farmers in the village (Tabia) would have received insurance payouts. Since the farmers could list a maximum of 5 years, the maximum possible value is 5. The second diagnostic, WOK, is based on the average of all the farmer interviews in the region (the Woreda). The WOK diagnostic is necessary because we assume that farmer discussions can have miscommunications and the average of several discussions may average away some of the errors. WOK is the number of years during which there would have been payouts in the 6 most mentioned bad years across the entire region. If a particular village interview was not effective, then one might expect the area level diagnostic to work better. But it could also be that there is a relatively lower TOK compared to the WOK because the village actually had a different experience than the rest of the region.

The timing of the windows used in the indexes for each village was suggested by the farmers in the village. The project used TOK and WOK as diagnostics to identify the need for future follow up. If they were particularly low, the timing of the index windows was modified to see if there were better options. If better options could not be found, or if there were big disagreements between TOK and WOK, this was mentioned to the local village team, and additional discussions occurred to make sure that they were willing to move forward with the product.

Table *Index Agreement with bad years reported by farmer groups in each village in 2010* presents the TOK and WOK diagnostics in a development phase of the indexes in an earlier stage of the project. When looking at the table, note that it is difficult to flag the Tanque Abergele region or Tsegea or Hawelti as being particularly problematic (in bold in the table *Index Agreement with bad years reported by farmer groups in each village in 2010*). If a problem had been identified, the indexes would have been changed to address issues raised. Many issues may already have been diagnosed by using this farmer data, leaving the remaining 3 problem areas to be identified using information not yet used in product design.

Table 5.5: Index Agreement with bad years reported by farmer groups in each village in 2010

Name	Woreda	TOK	WOK
Bethans	Adwa	3	5
DebreGenetA	Adwa	2	4
EndaBagerima	Adwa	2	3
Gendebta	Adwa	3	3
MariamShewito	Adwa	3	4
Seloda	Adwa	3	5
TahtayLegomti	Adwa	2	4
Wedikeshi	Adwa	4	5
Adiyikoro	Ahferom	3	5
Adizata	Ahferom	3	5
Betgebez	Ahferom	3	3
LaelayMegariaTsemri	Ahferom	4	6
Maysuru	Ahferom	5	6
Sero	Ahferom	4	6
TahtayDaeroka	Ahferom	2	5
TahtayMegariaTsebri	Ahferom	5	6
Gerjale	Alamata	4	5
KuluGizeLemlem	Alamata	1	3
LaelayDayu	Alamata	4	5
Limaat	Alamata	1	3
SelamBekalsi	Alamata	2	3
SelenWuha	Alamata	1	3
BarkaAdiswha	Atsbi	3	4
FelegeWayane	Atsbi	3	4
Golgolemalee	Atsbi	4	5
Habees	Atsbi	1	4
RubaFelege	Atsbi	3	5
AbrahaAtsbaha	KinteAwelo	4	5
AdiKisandid	KinteAwelo	2	5
Aynalem	KinteAwelo	5	5
Genfel	KinteAwelo	4	5
Kihen	KinteAwelo	2	5
MahbereWeyane	KinteAwelo	3	5
Mesanu	KinteAwelo	2	5
Nagash	KinteAwelo	4	5
AdiHa	KolaTembien	3	6
Atakilti	KolaTembien	3	7
AwetBikalsi	KolaTembien	3	6
Begashek	KolaTembien	1	4
DebreGenetK	KolaTembien	3	5
Endabano	KolaTembien	3	6
GetskiMilesiley	KolaTembien	4	6
Menji	KolaTembien	4	7
Werkamba	KolaTembien	3	6
AdisKigni	RayaAzebo	3	3
Bala	RayaAzebo	2	5

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Table 5.5 – continued from previous page

Name	Woreda	TOK	WOK
Ebo	RayaAzebo	1	4
Geneti	RayaAzebo	3	5
HadeAlga	RayaAzebo	3	5
Hawelti	**RayaAzebo**	**4**	**6**
Korme	RayaAzebo	3	6
Mechare	RayaAzebo	2	4
Tsigea	**RayaAzebo**	**4**	**6**
Ulaga	RayaAzebo	3	6
Agazi	SaesiTsaedaemba	3	5
Asmena	SaesiTsaedaemba	3	5
GuemseAgamet	SaesiTsaedaemba	2	5
HadushAdi	SaesiTsaedaemba	3	4
HadushHiwet	SaesiTsaedaemba	2	5
Hangoda	SaesiTsaedaemba	3	5
Sendada	SaesiTsaedaemba	3	5
Sinkata	SaesiTsaedaemba	2	5
AdekeAla	Samre	2	4
AdisAlemS	Samre	1	4
AmdiWeyane	Samre	2	4
HintsaWaza	Samre	3	4
MayTeklia	Samre	3	4
MetkelLemat	Samre	3	3
Agbe	**TanquaAbergele**	**1**	**5**
Gera	**TanquaAbergele**	**4**	**6**
ImbaRufael	**TanquaAbergele**	**3**	**6**
Lemlem	**TanquaAbergele**	**2**	**5**
Mearey	**TanquaAbergele**	**2**	**5**
Shekatekli	**TanquaAbergele**	**2**	**5**
AdisAlemW	WiereLahe	3	5
Endachiwa	WiereLahe	3	6
Endagahamus	WiereLahe	3	4
Maekelawi	WiereLahe	3	4
MaekelSegli	WiereLahe	3	5
Selam	WiereLahe	3	5
Zongi	WiereLahe	2	5
Golba	Ziway	5	5
Haleku	Ziway	5	5

Based on the project experiences since 2010 and the processes for community based discussions has been made much more systematic and improved, leading to more consistent results. Currently, when farmers raise concerns, or when the project is scaling to a new villages, we use our new materials. Figures 5.7, and 5.8 illustrate how these materials and more sophisticated activities are being applied for project scaling. In Figure 5.7 farmers are identifying their worst years in an interactive exercise facilitated by local project partners. Figure 5.8 shows the results of these discussions, which help improve the indexes. Given the scale of the R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) project, the new materials have not yet been systematically applied across all of the villages.

5.4.2 Farmer rain gauges

Another source of information for indicating problems are manual rain gauges monitored by farmers and experts in the villages. Across project sites, there are several hundred farmer monitored manual rain gauges. In the early project

Figure 5.7: Farmers discussing and presenting historical problem years in interactive exercise

Figure 5.8: Results from interactive exercise identifying problem years

villages, there are typically about 20 gauges. In some of the villages the coordinates of these gauges are known. However, because these gauges are new, they cannot provide historical data. It is difficult to communicate the daily rainfall from the gauges, clean the data, or assure its accuracy in a comprehensive real-time basis. Therefore, the most effective use of this data is to follow up on specific issues in specific places. When a complaint has been raised by a village, its rain gauge data is often discussed. In some cases, the project has gathered data to address specific project questions.

Figure 5.9 shows a project diagnostic comparing the satellite rainfall estimate over the 2010 late index window with the average of all of the farmer rain gauges in the village. The results from four villages are shown. Although the rainfall differs somewhat from the satellite estimate, in general, the relative amounts are similar between the gauges and the satellite, reflecting the differences in rainfall across villages.

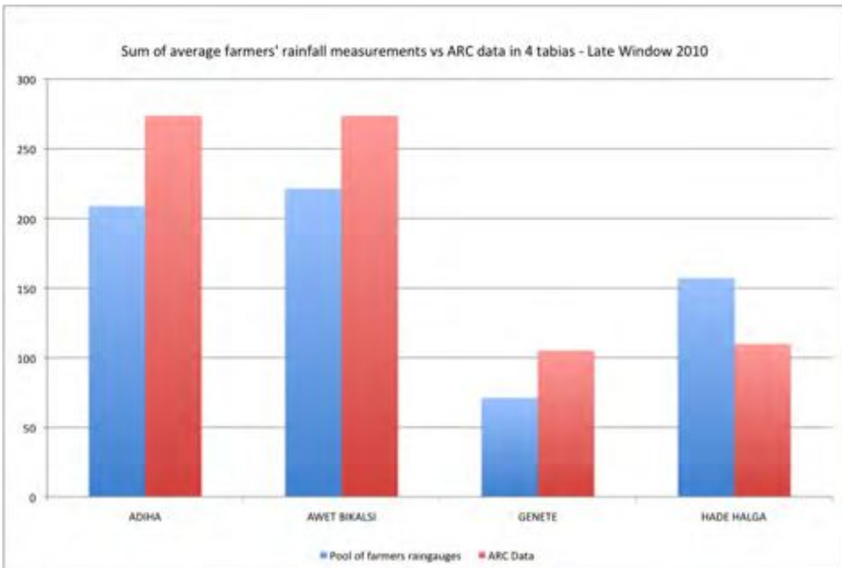

Figure 5.9: Average of farmer rain gauges compared to ARC, late window 2010

Figure 5.10 shows a related exercise aimed at understanding the variability within a village. It shows the average rainfall estimate from ARC compared to the averages of rainfall for each of the four Kushettes (sub-villages) in each village. The figure demonstrates the within-village variability, as well as a meaningful level of general agreement across the entire village.

5.4.3 Diagnostics using regional yield data

For some crops, regional level yield data was available. One such crop, was Teff, which is planted late in the season, and is therefore vulnerable to problems in the late window. Yield data is challenging to interpret, because there are many things that can impact yields but would not determine the insurance payouts, such as improving access to fertilizer or improvements in production practices. In addition, this data can have meaningful levels of error and missing years. Therefore, it's best used as a diagnostic, to identify issues for follow up to make sure that meaningful problems have not been ignored. Table *Comparison of Teff Yield to Average Late ARC Ranking by Woreda (Source Ethiopian Bureau of Agriculture and Rural Development)* shows the regional yield statistics as well as averaged normalized rankings of ARC rainfall during the late window for each region (1 means that was the year with highest rainfall, and 0.08 is the lowest rainfall year). One can see that production increases over time. According to the ARC estimates, farmer discussions, and other available information, 2004 was confirmed as a year with dramatic problems across the entire area, and 2009 was a year with many problems. In a typical insurance product, it is rare to have more than 2 payouts in a 10 year period, so agreement with these two years would indicate that the insurance would have done about as well as is expected for most products. 2010 was well known as having very good rainfall and very good yields

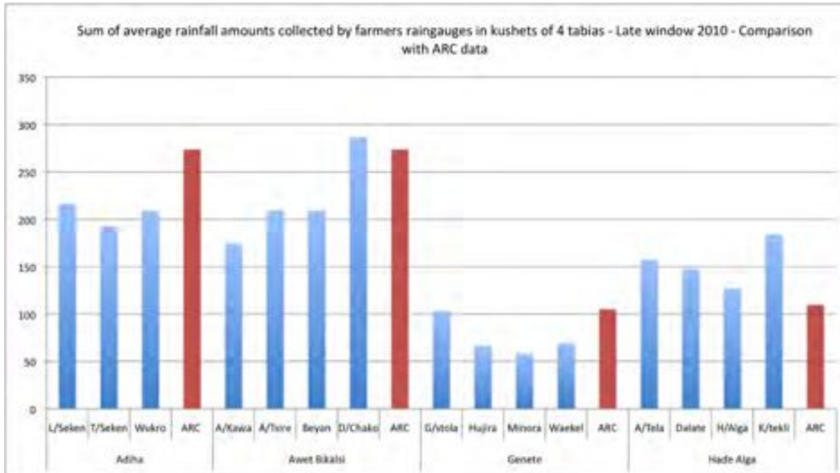

Figure 5.10: Breakdown of farmer rain gauge averages by subvillage (Kushet), late Window 2010

across the area. Looking at the column for 2004, it is clear that it provides the lowest yields for most regions, as well as the lowest ranked estimated rainfall, providing some verification of the index. 2010 is also clearly marked by high yields and high rainfall rankings. Note that Tanque Abergele does not appear to exhibit any special problems using this diagnostic.

Table 5.6: Comparison of Teff Yield to Average Late ARC Ranking by Woreda (Source Ethiopian Bureau of Agriculture and Rural Development)

Year	2003	2004	2005	2006	2007	2008	2009	2010
Adwa Teff Yield (q/ha)	5.75	9.66	10.00	9.04		15.00	15.33	18.27
Adwa Average Late ARC Ranking	0.97	0.18	0.92	0.49	0.70	0.42	0.10	0.80
Ahferom Teff yield (q/ha)	4.43	4.95	6.50			16.22	13.74	16.37
Ahferom Average Late ARC ranking	0.97	0.08	0.78	0.35	0.45	0.51	0.22	0.95
Alamata Teff yield (q/ha)	3.98	1.66	5.00			0.77	0.75	20.04
Alamata Average Late ARC ranking	1.00	0.08	0.45	0.28	0.61	0.86	0.17	0.83
Atsbi Teff yield (q/ha)	3.87	5.26	5.00			3.57	4.68	9.00
Atsbi Average Late ARC ranking	0.85	0.13	0.83	0.53	0.45	0.52	0.12	1.00
Kinte Awelo Teff yield (q/ha)	3.08	1.18	4.55	5.12		5.74	3.04	14.09
Kinte Awelo Average Late ARC ranking	0.55	0.08	0.82	0.61	0.76	0.42	0.17	1.00
Kola Tambien Teff yield (q/ha)	4.90	4.06	8.00			11.61	13.96	14.17
Kola Tambien Average Late ARC ranking	0.99	0.11	0.80	0.41	0.62	0.47	0.19	0.83
Raya Azebo Teff yield (q/ha)	1.50	0.75	3.10	9.06		0.77	1.56	14.02
Raya Azebo Average Late ARC ranking	0.95	0.09	0.52	0.33	0.65	0.83	0.17	0.87
Saesitsae Daemba Teff yield (q/ha)	5.31	2.00				2.60	3.21	8.23
Saesitsae Daemba Average Late ARC ranking	0.62	0.08	0.75	0.56	0.75	0.60	0.24	1.00
Tanqua Abergele Teff yield (q/ha)	2.29	1.50	3.00			3.68	3.63	6.31
Tanqua Abergele Average Late ARC ranking	0.97	0.10	0.65	0.51	0.88	0.76	0.28	0.85

5.5 Details: Analysis of vegetation products using high resolution satellites and ground-truthing

Earlier in this report we talked about how we used high resolution but infrequent satellite images to try to understand lower resolution, more frequent imagery, and a limited number of expert ground visits to validate the high resolution imagery. We provide more of the details of the activities and results in this section.

A major focus of this work has been to see how the Landsat product could be helpful in the verification process. Landsat is a satellite program producing high resolution visual images of the Earth. We have used two products here; one with a resolution of 30m across a pixel (Landsat TM) and one with a resolution of 2m across (QuickBird). Although Landsat is high resolution, it does not take images frequently enough to be directly useful in index insurance.

Using Landsat visual imagery has two benefits for this project:

1. It allows us to independently check the EVI satellite product. One of the most important aspects in index design is transparency and robustness. This analysis is key in allowing us to show that EVI has some physical basis and that it is a reliable measure for use in validation.
2. The very high resolution of Landsat TM means that it is useful in independently selecting pixels with a high level of vegetation.

5.5.1 Checking MODIS

Since a pixel measures the average of everything within it, drought would be reflected in nearby MODIS pixels quite differently, depending on exactly what is inside of the pixel. In addition, the vegetation indexes, such as NDVI and EVI, are engineered to model the photosynthesis of foliage, which is a complex nonlinear process that does not necessarily average consistently across different size areas. If the average of a small area into the size of a MODIS pixel is not linear, our method of averaging the landscape together may behave unpredictably. In fact, any strategy that uses vegetative imagery averaged over a pixel would need to be verified at each size pixel (or average of pixels).

The methods developed to compare Landsat TM and MODIS are at the cutting edge of research. To achieve our first goal, we have chosen to look at scaling. The aim of scaling is to check whether the output from a large pixel (e.g., a 250m pixel) is the same as the average of individual outputs from lots of small pixels (30m). It is important to note that there is no reason why a high resolution vegetation product and a low resolution one should scale because shadows from mountains, different land surfaces and scattering effects mean that the two products are actually measuring different things. However, this is a way of validating where MODIS does well. If the products do scale at a given location then it means that the coarse resolution MODIS is based on the same vegetative fraction as the fine resolution Landsat, which gives us confidence that there is a physical reason behind MODIS EVI results.

The specific process of comparing these datasets is called vicarious validation. Vicarious validation compares vegetation estimates from lower resolution imagery to comparable estimates from higher resolution sensors acquired at the same location and similar time. Our strategy was to vicariously validate 250m MODIS vegetation index values by comparison to 30m Landsat TM estimates and then to validate the Landsat estimates by comparison to meter-scale imagery where available. Since meter scale imagery resolves the individual landscape features observed in the field, the vicarious validation provides a direct quantitative comparison of individual features (e.g., trees, scrub vegetation, agricultural fields) to the aggregate vegetation index values provided by MODIS.

To perform this validation, we selected several 30km x 30km test-regions in the heart of the R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) zone (near Adi Ha and Mekele). This region is especially mountainous and contains many types of topography, including steep ridges, high plains and low valleys. Since topography may play a significant role in how light scatters and therefore how satellites register ground conditions, our hypothesis was that these variations in topography might yield sharply divergent results in Landsat and MODIS data. For instance, because the Landsat sensor has higher spatial resolution, and because Landsat imagery is linked with orography, we expect each individual Landsat pixel to have a stronger relationship with elevation at that point when compared to MODIS pixels which average over a larger area. To test the role elevation plays in affecting MODIS and Landsat results, we also incorporated data from the Shuttle Radar Topography Mission (SRTM), a digital elevation model (DEM), resampled to the same resolution as Landsat.

The result of this study show that for the study regions, MODIS and Landsat EVI values exhibit a strong linear relationship (r ~ 0.7) across all elevations, thus EVI was shown to scale in all the regions we looked at. This is a fortuitous outcome, since we aggregate EVI across different spatial scales.

5.5.2 Selecting vegetative pixels

We then employed a technique called linear spectral un-mixing to figure out how much vegetation there was in each MODIS pixel. Figure 5.12 shows 4 potential MODIS pixels over the R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) region (each is 250m in width). This shows that there is a large range of landscapes that could be captured inside each MODIS pixel, but also that the satellite records this information differently. For example trees and water tend to look very dark, roads and houses tend to look bright and that fields (at least when there are crops) look different than bare earth.

Spectral un-mixing takes advantage of this feature of satellite imagery. First, we referred to a global survey of the light profile of various land cover types, compiled by [Small2013]. We then looked at the profile of light in every location to see which land cover type it was previously determined to be. Finally, a map was made with the percentage of vegetation in each Landsat and MODIS pixel.

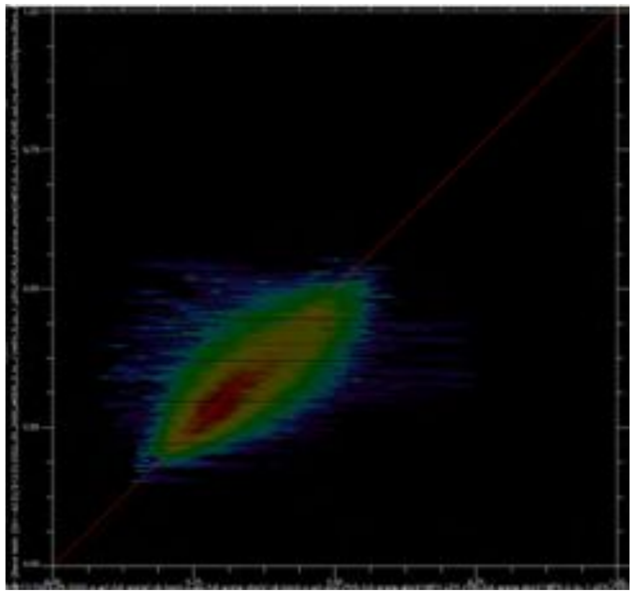

Figure 5.11: Density scatterplot of MODIS EVI (Y-Axis) and Landsat EVI (X-Axis) values for a sub-scene surrounding Adi Ha

Figure 5.12: Different types of land inside a single MODIS pixel. All of these pictures were gathered from inside the R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) insurance region using Google imagery.

This task was technically challenging because we had to do significant error checking of both the Landsat and MODIS pixels and convert both into a similar data formats.

5.5.3 Selecting EVI pixels instead of a simple box

The next question we have asked is whether we can use some method to only select EVI pixels containing vegetation.

As discussed above, MODIS EVI has a pixel size of 250m x 250m, which at more than six hectares (about 15 acres), is larger than most smallholder farmers' plots. Any given pixel used for index insurance contract design may therefore encompass non-farm land cover, affecting the pixel's vegetation index readings and rendering them less informative about actual crop health. Our initial solution was to use a higher resolution satellite product, but contamination by clouds and the infrequency of readings made this unworkable. So instead, we decided to find out how much vegetation was contained within each MODIS EVI pixel in order to only take places which grew crops into account. One important issue to keep in mind when interpreting vegetative fraction, is that it is a combination of the actual real estate covered by foliage, and how "rich" that foliage is. If the foliage is richer, it increases the vegetative fraction even if it covers the same area as less rich vegetation.

Finding out how much vegetation each MODIS EVI pixel contains is a difficult task in Africa. Unlike other regions in the world, in Africa there is very little commercial or large scale farming, which usually gives rise to large easily defined fields. Instead, there are thousands of small farms, each of which might have many different crops, trees, or livestock in the same small place on the edge of a village. In places such as Tigray, our job is even more difficult due to the complexity of the terrain and that there are often regions with bare earth. The difficulty of identifying the vegetative locations in Ethiopia is reflected in the fact that a good quality land use map does not exist for the country, thus we needed to figure out how much vegetation is in each pixel from scratch.

Our first approach was to explore simple within sample diagnostics. We know that plants respond to rainfall, so we postulated that if we could use the full correlation (e.g., not just the ranking with bad years) between ARC rainfall and EVI, it might help identify regions with vegetation. Working with remote sensing data is often computationally complex, using Terabytes of data, and is even more difficult due to the fact that remote sensing data can often contain significant errors that need correcting. An advantage therefore of choosing a simple correlation approach is that it allowed us to set up the computer systems to process more sophisticated methods of identifying vegetative pixels.

Two diagnostics were performed

1. We used some threshold of total correlation e.g., we only include EVI pixels in the analysis which have a correlation of over 0.8.
2. We weighted the pixels using the correlation e.g., we include all the pixels, but the ones with a correlation of 0.8 would count for 80% and the ones with a correlation of 0.1 would only count for 10% of the total EVI.

The two approaches showed slightly different results. The threshold approach showed very little change no matter what the threshold was set to. The weighted pixel approach however showed a much better correlation in some regions, and a worse ranking statistic in others as shown in Figure 5.13. Because the correlation between EVI and ARC rainfall is statistically close to our validation ranking statistic, we did not deem these results statistically robust enough to be explored in future work. Nonetheless, it was promising to see that our computer systems were set up correctly. Instead we wanted to use a more physical measure of vegetation which was unrelated to our ranking statistic. As a result, we also performed some initial explorations of using vegetative fraction estimates.

For QuickBird, IKONOS, and Landsat TM, it is feasible to perform analysis that determines the *vegetative fraction* in each pixel. The vegetative fraction is percent of the pixel that is covered by leafy foliage, as opposed to shadows, bare soil, water, or other things. If we are using the response of vegetation to rainfall to identify droughts, it is likely that a pixel that is mostly bare soil, shadows, or water will not give us the information we need. We calculated the vegetative fraction for QuickBird, IKONOS, and Landsat TM, and calculated the EVI for each satellite (MODIS, QuickBird, IKONOS, and Landsat TM). We compared the vegetative fraction to the EVI of each satellite, and aggregated the EVI and vegetative fraction from the fine resolution satellites to the coarser resolution ones, comparing results at each scale. Although our quick diagnostics did not find immediate improvements, it is possible that with more work we

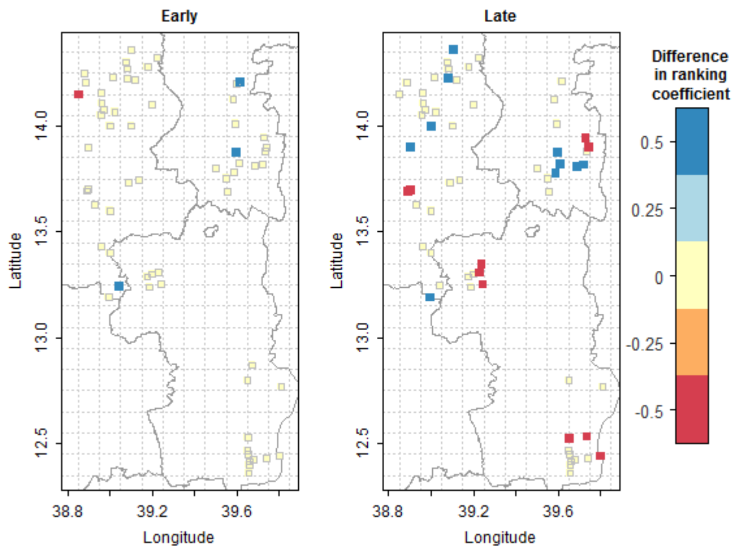

Figure 5.13: This shows whether using pixels weighted using the full correlation between EVI and ARC rainfall improves the ranking coefficient.

will eventually be able to better understand droughts by paying more attention to pixels that have more vegetation than those with more bare earth.

5.6 Details: Assessment of index and validation process using the experience of the 2012 drought

To better understand how the vegetative satellite products behaved in 2012, take a look at Table *Early season rainfall estimates for 6 tabias visited by the IRI team in 2012*, which shows the rankings of rainfall and the vegetative products in the early window for 2012 and Table *Late season rainfall estimates for 6 tabias visited by the IRI team in 2012*, which shows the for the late windows.

Table 5.7: Early season rainfall estimates for 6 tabias visited by the IRI team in 2012

Woreda	Tabia	ARC	TAMSAT	ENACT	EVI	NDWI
		Rainfall Product	Rainfall Product	Rainfall Product	Vegetation Product	Vegetation Product
KinteAwelo	AbrahaAtsbaha	0.69	1	1	0.77	0.77
KolaTembien	AdiHa	0.77	0.54	0.85	0.15	0.31
RayaAzebo	Hawelti	0.77	0.77	0.77	0.77	0.77
RayaAzebo	Tsigea	0.77	0.77	0.77	0.77	0.77
SaesiTsaedaemba	Agazi	0.54	0.92	0.85	1	0.92
SaesiTsaedaemba	HadushAdi	0.85	1	1	0.85	1

Table 5.8: Late season rainfall estimates for 6 tabias visited by the IRI team in 2012

Woreda	Tabia	ARC	TAMSAT	ENACT	EVI	NDWI
		Rainfall Product	Rainfall Product	Rainfall Product	Vegetation Product	Vegetation Product
KinteAwelo	AbrahaAtsbaha	0.15	0.15	0.77	0.08	1
KolaTembien	AdiHa	0.23	0.25	0.54	0.08	0.85
RayaAzebo	Hawelti	0.23	0.08	0.69	0.08	0.23
RayaAzebo	Tsigea	0.23	0.08	0.77	0.08	0.23
SaesiTsaedaemba	Agazi	0.15	0.08	0.85	0.08	0.85
SaesiTsaedaemba	HadushAdi	0.15	0.08	0.85	0.08	0.77

- In northeastern Tigray, for example in the eastern highland woredas of Kinte Awelo, Saesi Tsaedaemba, and Atsbi, farmers received low rainfall and received medium to full payouts based on ARC satellite-based indexes. When we look at the late season for these woredas, we can see good agreement between ARC and EVI with a low rainfall/vegetation ranking between for both.
- In the southern region of Tigray, in the lowland woredas of Raya Azebo and Alamata, farmers experienced one of their worst years on record. If we look in the late season , ARC and EVI estimates generally indicate low rainfall/vegetation ranking (0.08-0.25) for these woredas. On average, EVI indicates that for these two woredas, 2012 has been one of the worst years in the 12-year period considered in this report. 2012 was an extreme year in the eastern highland and lowland regions, and the EVI vegetation product corresponds well to the ARC rainfall product for 2012 in these regions.
- Conversely in the midland woredas of Ahferom, Kola Tembien, Samre and Tanqua Abergele, farmers experienced low to medium rainfall that warranted small to medium payouts. If we look at the results for the late season for these woredas, ARC and TAMSAT rainfall estimates generally indicate a rainfall ranking of 0.25-0.60. EVI estimates, on the other hand, indicate a lower vegetation ranking (0.08). Vegetation satellite estimates are good at detecting severe years because vegetation "turns brown." In less severe years it is challenging for vegetation satellite products to reliably detect dry conditions because changes in vegetation are more subtle.
- Based on the R4 Rural Resilience/Horn of Africa Risk Transfer for Adaptation (HARITA) experience in 2012, we have more confidence in the performance of EVI at detecting drought at the end of the season.
- ENACT and NDWI rankings did not perform as accurately in capturing farmers' experiences in 2012. For ENACT this is probably because there are some rain gauges that are not operational across all of the years, making year to year comparisons difficult. ENACT was much more valuable in understanding the evolution of the season, as was discussed earlier.
- **It is more challenging for EVI vegetation satellite product to identify the less extreme years. In the comparisons we can see that there is less agreement between EVI and ARC during the less extreme years.** Earlier we discussed how the EVI satellite vegetation product was found to be more skillful at determining extremely dry years (e.g., the type of years that would trigger a large payout), compared to less extreme ones, which might trigger small payouts. This was further investigated in our study of the late season in 2012, when the drought affected different areas within the region to a different extent. EVI was found to agree well with ARC in regions where there was a severe drought and full payouts, but less in regions where the drought was milder with partial payouts. Vegetation satellite estimates are good at detecting severe years because the entire landscape often "turns brown." It appears that in less severe years it is challenging for vegetation satellite products to reliably detect dry conditions because changes in vegetation are more subtle.

CHAPTER SIX

OVERVIEW OF COMMON SATELLITE PRODUCTS

Below is a summary of some of the most widely available satellite rainfall estimates, including some that we have not used in our comparisons.

6.1 Overview of Common Rainfall Products

1) RFE (African Rainfall Estimation):

The Climate Prediction Centre (CPC) African Rainfall Estimate (RFE) is a merged gauge-satellite precipitation dataset and has been developed as part of the Famine Early Warning System Network (FEWS-NET) project. The operational product went through a major change in 2001, from V1.0 to V2.0.

Instruments

- The 10.8 micro-meter infra-red channel on the METEOSAT satellite, measuring cloud top height.
- GTS rain gauge data (~ 2534 stations over Africa, but many that don't report each day. See Figure 6.1 for an example on the 21st February 2012)
- Passive microwave rainfall estimates take from the Special Sensor Microwave/Imager (SSM/I). This tells you about cloud composition and is taken at 6-hour intervals with a resolution of 0.25 degrees.

Note, RFE2 obtains the final daily rainfall estimation using a two part merging process, then sums daily totals to produce dekadal (10 day) estimates at about 10km spatial resolution.

2) NOAA-RFE2 - ARC (Africa Rainfall Climatology):

ARC is also produced by NOAA-CPC at 10km spatial resolution daily. It is very similar to RFE except that 3-hourly TIR data is used instead of 30-minute data and it does not include MW observations. While the original ARC1 dataset was available starting from 1995, ARC has recently been updated to ARC2, which now provides rainfall data going back to 1983. Data is available 1 month after the event.

3) TAMSAT (and TARCAT)

The Tropical Applications of Meteorological information from SATellites research group (TAMSAT) is based at the University of Reading. TAMSAT data is available from www.met.reading.ac.uk/~tamsat or from national meteorological agencies.

Instruments

- The 10.8 micro-meter infra-red channel on the METEOSAT satellite, measuring cloud top height.

The TAMSAT product is unique in that it uses a local calibration, which takes into account the expertise of African meteorological agencies and allows it access to a large amount of historical data [TAMSAT]. In addition, because it only uses one instrument, the TAMSAT product has been made into a 30 year time-series (from 1983 to present) called TARCAT [TARCAT], which does not suffer from changes in instruments affecting the time-series.

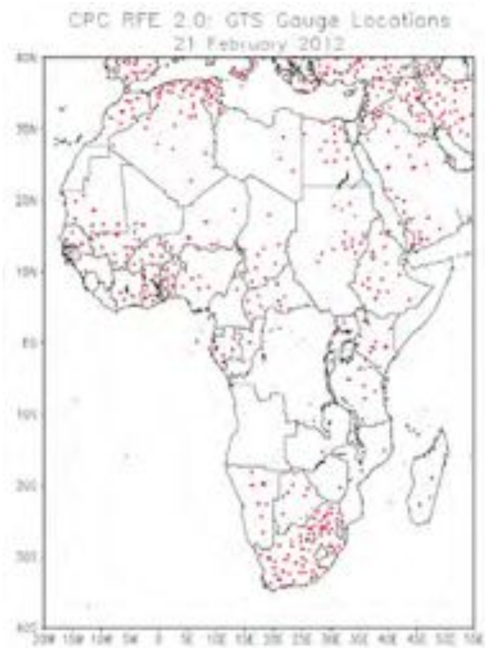

Figure 6.1: WMO GTS rainfall data available on the 21st February 2012. Up to 2534 stations report to the GTS network, but many do not report every day. This information is used in the NOAA RFE satellite product. Image courtesy of NOAA RFE

4) Ethiopia ENACT (Enhanced Climatology Time Series for Ethiopia):

The Ethiopia National Meteorological Agency (ENMA), TAMSAT and IRI, with funding from Google.org, have worked to create an Enhanced Climatology Time Series (ENACT) for Ethiopia.

This was created using a two step process. Firstly, TAMSAT and ENMA performed a detailed calibration of the relationship between cloud top height and rainfall amount using over 1000 Ethiopian rain gauges. Then IRI and ENMA merged these gauges with the satellite rainfall estimate. A similar process was carried out for temperature.

- Enhanced national climatology based on 30 years of good quality 10- daily rainfall and temperature for every 10km by 10km grid;
- An online mapping service (using the IRI Data Library) installed at the National Meteorological and Hydrological Services (NMHS), providing user-friendly tools for visualization, querying, and accessing information products. The Climate Analyses and Applications Map Room can be accessed here: http://www.ethiometmaprooms.gov.et:8082/maproom/

5) TRMM (Tropical Rainfall Measurement Mission) Combination: The Tropical Rainfall Measuring Mission (TRMM) is a joint mission between NASA and the Japan Aerospace Exploration Agency (JAXA) designed to monitor and study tropical rainfall. TRMM data is available from http://trmm.gsfc.nasa.gov/ .

Instruments

- A precipitation radar (PR), which provides high resolution information on the intensity and distribution of the rain, on the rain type, on the storm depth and on the height at which the snow melts into rain.
- TRMM Microwave Imager (TMI). The TMI is a passive microwave sensor designed to provide quantitative rainfall information over a 878- kilometer wide swath underneath the satellite. The TMI is able to quantify water vapour, cloud vapour, cloud water and rainfall intensity. It is the workhorse of the TRMM satellite.
- Visible and Infra-red Scanner (VIRS)

Due to the number of instruments it uses, the methodology behind TRMM is relatively complex. Two useful products include

3B42: 3-hourly or daily merged satellite / gauge product. This is available from 60N-60S from 1998. Present day and is available one month after the event. The resolution is 0.25 x 0.25 degrees (so roughly 30km by 30km)

3B42-RT : 3 hourly or daily satellite only product. Available from 60N - 60S from 1998 - Present day and available in real time. Available at a resolution of 0.25 x 0.25 degrees. The resolution is 0.25 x 0.25 degrees (so roughly 30km by 30km)

TRMM can be very challenging to compare between time periods because of the complexity of the product.

Below are descriptions of some of the most common vegetative satellite products, including products we do not utilize in our comparisons.

The first three products are based on the Normalized Difference Vegetation Index (NDVI), the most widely used satellite-based vegetative index. NDVI senses the greenness in a given area by comparing the radiation reflected in the visible (red) and near-infrared (NIR) bands. This provides a sense for plant photosynthesis levels, or their chlorophyll (‘greenness’) and biomass.

6.2 Overview of Common Vegetation Products

1) NDVI/AVHRR (Advanced Very High Resolution Radiometer):

The NOAA AVHRR satellites take measurements at an 8km spatial resolution and provide global coverage on an almost daily basis. An NDVI product is then aggregated on a 10 day and monthly basis for Africa. In addition, new investment in the global AVHRR data record has enabled reprocessing using improved techniques that have enhanced the resolution of the data to 4km globally since 1981. This long time period allows the identification of local and sub-regional drought patterns and enables identification of the worst drought years in order to establish index insurance policies. However, it is an early product with many known limitations. In addition, there are many substantial changes that have occurred during the product lifecycle that make it very difficult to perform reliable comparisons between years. This product is no longer operational, so it can be helpful for for historical analyses if attention is paid to the changes in the product over the years.

2) NDVI/MODIS (the MODerate resolution Imaging Spectroradiometer):

NDVI/MODIS is a vegetation index produced by the National Aeronautical and Space Administration (NASA). The MODIS sensor (on NASA’s Terra satellite) provides almost daily global coverage (the same frequency as AVHRR), but at a much finer spatial resolution (250m). The NDVI/MODIS product it provides is a 16-day composite index, and is a source of higher quality NDVI products than that provided by the AVHRR sensors. Recent investments by the US Department of Agriculture will soon result in a global NDVI product with a 9-hour delay and a 500m resolution, which will enable rapid analysis of crop conditions.

3) NDVI/SPOT (SPOT Vegetation Index):

This NDVI product from the French Centre Nationale d’Etudes Spatiales (CNES) is measured every day and aggregated on a ten day basis at a 1km spatial resolution. This product uses similar measurements to that of NDVI/MODIS, however these are provided at a different spatial resolution.

The fourth and fifth vegetative index products measure the radiation reflected by slightly different bands than those used in NDVI products, which allows them to estimate different features of vegetation on the ground. These are:

4) EVI/MODIS (Enhanced Vegetation Index):

This vegetative index is derived from the same satellite source as NDVI/MODIS. While the EVI is calculated similarly to NDVI, it makes some adjustments and also incorporates additional information from other radiation bands (specifically visible blue light), which allows it to correct for some distortions in reflected light due to atmospheric haze as well as the land surface beneath the vegetation. EVI is also more sensitive to canopy structure and type than NDVI, and thus it is more sensitive to differences in heavily vegetated areas.

5) NDWI/MODIS (Normalized Difference Wetness Index):

The NDWI vegetative index is also derived from NASA's MODIS sensor (the same source as NDVI/MODIS), but measures the radiation reflected by different bands than NDVI products in order to capture changes in vegetation water content. Specifically, NDWI measures reflected radiation in the near-infrared (NIR) and short-wave infrared (SWIR) bands, since reflectance in the SWIR band helps to determine the amount of water present in leaf internal structure. SWIR radiation occurs at slightly longer wavelengths than NIR or visible light.

In terms of data availability, the MODIS-derived indexes (numbers 2,4 and 5) are only available starting from the year 2000, while NDVI/SPOT-VEGETATION data is available from 1998. NDVI/AVHRR is available starting from 1981.

CHAPTER SEVEN

GLOSSARY

Some commonly used phrases and acronyms.

Table 7.1: ILO Glossary

Term	Meaning
ARC	A 30 year time-series of data from the NOAA-RFE2 rainfall satellite (1983 - present day)
Basis risk	The risk inherant to index insurance, that means that a farmer may suffer loss but the index does not trigger a pay-out
EVI	Enhanced Vegetation Index. A sophisticated vegetation index designed to work well in areas with high biomass and vegetation
Exit	If there is less rainfall than this value, then a full pay-out will be provided
LANDSAT	A satellite which takes high-resolution visual images of the Earth
MeteoSat	A weather satellite which captures infra-red and visible photos of clouds. All the rainfall estimates used here come from MeteoSat
MODIS	Moderate-resolution Imaging Spectroradiometer. A satellite instrument which captures many of the images needed for vegetation indices
NDVI	Normalized Difference Vegetation Index (NDVI) is a simple vegetation index which can be used to assess whether the target being observed contains live green vegetation or not.
NDWI	Normalised Difference Water Index is a vegetation index designed to assess the water content in live green vegetation
NOAA RFE2	A satellite rainfall product which uses both images of clouds and microwaves to estimate rainfall
Pixel	The smallest area ‘viewed’ by a satellite. So a pixel size of 10km x 10km would mean that the satellite can only take one reading every 10km x 10km
Scaling	How to turn a small pilot index insurance scheme into one that operationally covers many more
Site	A single location used in the operational index insurance scheme. This is typically a village and there will be one index per site
TAMSAT	A satellite rainfall product which uses both images of clouds to estimate rainfall. It is also locally calibrated
Trigger	If there is less rainfall than this value, then a pay-out will be provided
Vegetation index	An estimate of some aspect of vegetation (e.g. how green it is, how much water it contains etc)

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